Psychological Bulletin

ISSN: 0033-2909

2022, Vol. 148, Nos. 7–8, 555–587
https://doi.org/10.1037/bul0000375

In Which Environments Is Impulsive Behavior Adaptive? A Cross-Discipline Review and Integration of Formal Models

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Are impulsive behaviors an adaptive response to living in harsh or unpredictable environments? Formal models help address this question by providing cost–benefit analyses across a broad range of environmental conditions, but their various results have not been systematically integrated. Here, we survey models from diverse disciplines including psychology, biology, economics, and management to develop a conceptual framework of impulsivity. Using this framework, we integrated results from 30 models to review whether impulsivity is adaptive across a range of environmental conditions. We focus on information impulsivity, that is, acting without considering consequences, and temporal impulsivity, that is, the tendency to pick sooner outcomes over later ones. Results show that both types are adaptive when individuals are close to a critical threshold (e.g., bankruptcy), resources are predictable, or interruptions are common. When resources are scarce, impulsivity can be adaptive or maladaptive, depending on the type and degree of scarcity. Information impulsivity is also adaptive when environments do not change over time or change very often (but maladaptive in between), or if local resource patches have similar properties, reducing the need to gather further information. Temporal impulsivity is adaptive when environments do not change over time and when local resource patches differ. Our review shows theoreticians how ideas from different disciplines are connected, affords formal modelers to see similarities and differences between their own models and those of others, and informs researchers about which empirical predictions generalize across a broad range of environmental conditions and which ones do not. To end, we provide concrete recommendations for future empirical studies.

Public Significance Statement
We review and synthesize findings from 30 formal models from diverse disciplines to evaluate whether impulsive behaviors are adaptive or maladaptive in harsh or unpredictable environments. We focus on information impulsivity, acting without considering consequences, and temporal impulsivity, choosing sooner outcomes over later ones. Our synthesis provides six broad conclusions on the adaptive value of information and temporal impulsivity in different environmental conditions. We also provide recommendations for future research on environmental influences on impulsive behaviors.

Keywords: information impulsivity, temporal impulsivity, harshness, unpredictability, formal modeling

Supplemental materials: https://doi.org/10.1037/bul0000375.supp

There are broadly two common perspectives on impulsive behaviors. The first considers impulsive behaviors as poorly conceived, prematurely expressed, unduly risky, or inappropriate to the situation, often resulting in undesirable outcomes for long-term health and well-being (Baumeister, 2002; Daruna & Barnes, 1993; de Wit, 2009; Duckworth, 2011; Evenden, 1999; Moffitt et al., 2011; Verdejo-García et al., 2008). There is empirical evidence to support this perspective. Most famously, in Walter Mischel's landmark

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The authors would like to thank Ethan Young, Esther Weijman, and various researchers of the Behavioral Science Institute (BSI) at the Radboud University for their helpful comments and suggestions on previous versions of this article. Willem E. Frankenhuis's contributions have been supported by the Dutch Research Council (016.155.195 and V1.Vidi.195.130), the James S. McDonnell Foundation (https://doi.org/10.37717/220020502), and the Jacobs Foundation (2017 1261 02). The authors have no conflict of interest to disclose.
Data and methods are available at https://osf.io/m2fp6/.
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marshmallow studies, children were given a choice between taking a single marshmallow now or waiting and receiving two marshmallows after a short delay (Mischel et al., 1989). Children who were impulsively unwilling to wait were more likely to have negative outcomes later in life, including lower academic achievement, unstable social relationships, higher rates of crime and incarceration, and decreased life expectancy (Moffitt et al., 2011). Impulsive behaviors have also been associated with a host of other negative outcomes, such as insufficient saving for retirement (Benartzi & Thaler, 2007), unhealthy lifestyles including obesity and smoking (Chabris et al., 2008; Courtemanche et al., 2015; Khwaja et al., 2007), and ecological pollution (Hardisty et al., 2013; Read et al., 2017). Understandably, educators, social workers, and policy-makers have designed interventions to reduce impulsivity, with the goal to promote long-term health, well-being, and educational outcomes (Diamond & Lee, 2011).

Although these researchers emphasize that impulsive behaviors tend to have long-term costs, they recognize that impulsivity can, in some cases, bring short-term benefits (Shah et al., 2012). For example, in conditions of hardship, such as having insufficient money to pay the rent, impulsive behaviors can help to "make ends meet" (Daly & Wilson, 2005; Frankenhuis & Nettle, 2020; Frankenhuis et al., 2016; Kruger et al., 2008). Despite short-term benefits, such actions often create, or exacerbate already existing, long-term problems. For instance, taking a high-interest loan might cover the rent of this month, but this debt needs to be repaid, reducing the available resources in the next months, limiting in turn income that can be invested in long-term education or health (Shah et al., 2012). Accordingly, the common view in the social sciences is that, across an individual's lifetime, the costs of impulsive behaviors outweigh their benefits.

The second perspective emphasizes that impulsive behaviors can be beneficial overall, across both the short-term and long-term, in some conditions. For instance, if the future is uncertain, an impulsive short-term orientation may allow an individual to act swiftly and seize fleeting opportunities. Over time, these small affordances add up, resulting in long-term benefits. Consider a taxi driver in a busy urban area, where long-term income depends on many unpredictable factors. An impulsive taxi driver who makes fast decisions can capitalize on unexpected opportunities, even if fast decision-making increases the risk of accidents. Over the course of a career, these small affordances add up, increasing total long-term income. Some taxonomies explicitly distinguish between *dysfunctional* impulsivity, which is long-term net costly, and *functional* impulsivity, which is long-term net beneficial (Dickman, 1990). Two lines of empirical research suggest that impulsive behaviors can indeed be adaptive overall through short-term and long-term benefits.

First, recent studies suggest that the relation between behavior in the marshmallow task and later-life outcomes is more complicated. Indeed, Walter Mischel himself viewed impulsivity as adaptive in some conditions (Shoda et al., 1990). For instance, children wait less if they have been led to believe that the larger payoff associated with waiting is unlikely to materialize (Kidd et al., 2013; Lee & Carlson, 2015; Moffett et al., 2020). In line with these experimental findings, a recent large-scale replication suggests that much of the association between impulsivity and negative life outcomes disappears when controlling for the harshness of the child's early environment (Watts et al., 2018; but see also Falk et al., 2020).

Second, in harsh environments where there are higher levels of threat and deprivation, impulsive behaviors such as violent crime and sexual promiscuity come with costs, but they also can boost social status and increase the number of sexual partners and children (Hawley, 1999; Yao et al., 2014). Similarly, impulsivity is associated with an increased rate of pregnancy during adolescence (for a meta-analysis, see Dir et al., 2014). Adolescent pregnancy is often associated with lower health and lower educational outcomes (Geronimus, 1997). Despite costs, there can also be benefits to adolescent pregnancy in low socioeconomic environments, for instance, some studies have found higher birth weight and lower infant mortality (Frankenhuis & Nettle, 2020; Geronimus, 1997, 2004; Moore & Snyder, 1991; Rich-Edwards et al., 2003). If resources are low, material and social support from grandparents can help with daily hardships. However, people living in poverty are less likely to reach old age in good health, meaning that older grandparents may have less resources to give. Therefore, rather than delaying reproduction, there may be benefits to having children early, while children's grandparents are still capable of providing support (Geronimus, 1997, 2004).

The perspective that impulsive behaviors can be beneficial in the long term is rooted in the idea that humans have evolved decision-making mechanisms that enable them to respond adaptively to harsh and unpredictable conditions. A recent synthesis of evidence from history, anthropology, and primatology shows that over human evolution, people have been exposed to higher levels of threat and deprivation (e.g., resource scarcity, uncontrollable mortality) than is typical in industrialized societies, and there has been substantial variation in the extent of these challenges across space and time (Frankenhuis & Amir, 2022; see also Humphreys & Salo, 2020). For instance, an analysis of small-scale and geographically and culturally diverse historical societies suggests that before the advent of agriculture, more than a quarter of people born did not survive their first year of life, and nearly half did not survive to puberty, with some of the survivors suffering disability (Volk & Atkinson, 2013; for surveys focusing on small-scale societies, see Gurven & Kaplan, 2007; Hewlett, 1991; Walker et al., 2006). These challenging conditions likely favored a high degree of phenotypic plasticity, the ability to tailor development and behavior to different conditions, including harsh and unpredictable environments.

Though there is evidence that impulsive behaviors can be adaptive in some conditions, it remains an open question what those conditions are. Impulsive behaviors have both short- and long-term costs and benefits, and these are difficult to quantify and compare. Here we ask: In what conditions do we expect that overall benefits outweigh costs (making impulsivity adaptive), and when do we expect overall costs outweigh benefits (making impulsivity maladaptive)? To answer this question, we survey the literature on the costs and benefits of impulsive behavior in a range of environmental conditions. Using this survey, we synthesize theoretical insights from diverse disciplines including psychology, biology, economics, and management. We perform this theoretical synthesis over a set of formal models, akin to how a meta-analysis synthesizes empirical studies. Before defining specific formal models and explaining the approach we follow in the rest of the article, we first discuss why formal models are an important contribution to the study of impulsive behavior. Specifically, they help address two limitations that hinder research on adaptive impulsivity: conceptual confusion and practical limitations.

Conceptual Confusion: Towers of Babel

The term “impulsivity” is used in the literature to cover a wide variety of cognitive and behavioral constructs (Strickland & Johnson, 2021). Although the components and structure of impulsivity remain a topic of debate, classification schemes often distinguish between impulsive choice, inattention, and impulsive action (for a nonexhaustive list of classification schemes, see Supplemental Material 1).

Impulsive choice refers to which option an individual selects. Impulsive choice can be divided into two constructs: temporal impulsivity and information impulsivity. *Temporal impulsivity* is the tendency to select sooner outcomes over later ones, even if later outcomes are more rewarding. This form of impulsivity is also known as temporal discounting (Caswell et al., 2015), choice impulsivity (Fineberg et al., 2014; Hamilton, Mitchell, et al., 2015), or the inability to delay gratification (Dick et al., 2010). *Information impulsivity* is the tendency to act without fully understanding the consequences of one’s actions, even though these consequences are knowable. This form of impulsivity is also known as a lack of premeditation or preparation (Cyders et al., 2007; Evenden, 1999), nonplanning impulsivity (Dick et al., 2010; Patton et al., 1995), or reflection impulsivity (Caswell et al., 2015; Fineberg et al., 2014). The classification schemes in Supplemental Material 1 differ in whether they consider choice impulsivity as a preference (i.e., wanting to act impulsively) or as (a tendency) to behave impulsively. We use the latter, defining impulsivity as a tendency for behavior rather than a preference.

Inattention plays a role when selecting which action to take. Individuals high in inattention are easily distracted and unable to focus at the task at hand (also known as a lack of persistence or perseverance: Cyders et al., 2007; Dick et al., 2010; Evenden, 1999; Patton et al., 1995; Whiteside & Lynam, 2001).

Impulsive action takes place after a decision is made. An individual high in impulsive action is unable to suppress—or cancel already activated—incorrect but dominant motor patterns (de Wit, 2009; Evenden, 1999; Reynolds et al., 2006). This form of impulsivity is also known as motor impulsivity (Caswell et al., 2015; Fineberg et al., 2014; Patton et al., 1995) or urgency (Cyders et al., 2007; Dalley et al., 2011; Whiteside & Lynam, 2001).

It creates problems when a single label is used to denote different types of impulsivity because these types pose different challenges: They have different costs and benefits and thus can be adaptive in different conditions. Consider information and temporal impulsivity in a resource-scarce environment. In such environments, the few available job opportunities are quickly filled by others. Spending time to contemplate which vacancy to apply for likely results in the vacancy being filled by someone else. An informationally impulsive individual acts more quickly to seize such fleeting opportunities. Moreover, in a resource-scarce environment, one’s monthly income may be lower. This means that immediately spending available income on nonessential goods (i.e., temporal impulsivity) might make it difficult to pay rent at the end of the month. Thus, in this particular environment, some types of impulsivity may be adaptive (e.g., information impulsivity) and others not (e.g., temporal impulsivity), making it critical to distinguish between different types of impulsivity.

There is also the opposite challenge: different labels being used to denote the same type of impulsivity (Whiteside & Lynam, 2001). This happens in part because impulsivity is studied in different disciplines that use different terminologies. For instance, a cognitive psychologist studies how deliberation affects well-being. Deliberation takes time, but it reduces uncertainty about consequences. An organizational psychologist studies how people search for jobs. The first job offer provides immediate income, but searching longer might result in opportunities that are more fulfilling in the long term. A biologist studies an animal that seeks to maximize its caloric intake. This forager can either stay in its current patch and receive a known but small reward or move on in search of greener pastures and bigger rewards. An economist studies how company policies affect profit. Investing in new ventures early on results in sooner outcomes but increases the risk of investing in assets that might fail. Although it may seem as though these four scholars’ study different decisions, there are important similarities. They all focus on a single individual facing trade-offs between immediate and future outcomes (temporal impulsivity); options with known and unknown consequences (information impulsivity); and an environment that shapes which behaviors are adaptive. Emphasizing shared features builds bridges between scientific disciplines and advances our understanding of general theoretical principles (Hills et al., 2015).

Limitations of Empirical Research

Empirical research faces practical limitations in terms of what environments, behaviors, and timescales can be studied. These practical limitations constrain what can be learned about commonalities and differences between different types of impulsivity and their consequences in different environmental conditions. It is both difficult and unethical to randomly assign humans to variations in harsh and unpredictable environments, especially for any extended time window (i.e., longer than a brief experimental session). This makes it difficult to determine causality. Do harsh and unpredictable environments lead to high levels of impulsivity because such levels are adaptive in these environments? Or does impulsivity increase the likelihood that people end up in such environments, even if it is maladaptive in these conditions?

Even when some practical limitations are lifted (e.g., in “natural experiments”), there will be other limitations to what empirical research can teach us about the effects of environment on behavior. In particular, environments typically differ on multiple dimensions that tend to covary (Smith & Pollak, 2020). For example, compared to people in affluence, people in poverty tend to have not only a lower average income but also tend to experience less stability in income, higher rates of crime, and higher levels of disability and disease. This creates two challenges. First, the effects of different environmental dimensions on the adaptive value of impulsivity may interact. For instance, temporal impulsivity might be adaptive if the environment changes little over time, theft is common, and resources are scarce. Such interactions make it difficult, if not impossible, to understand the isolated effect of any single dimension. Second, if dimensions tend to covary (e.g., low-income neighborhoods tend to have higher rates of crime), naturalistic designs are unable to isolate the effect of individual dimensions.

The Benefits of Formal Models for Impulsivity Research

Formal models can help address both challenges. First, they can increase conceptual clarity by providing explicit definitions of concepts and their relations. Second, they allow us to analyze the ways in which environmental conditions shape costs and benefits of different types of impulsivity. Several recent publications provide accessible discussions of the goals, practice, and necessity of formal modeling for the social sciences in general and psychology in particular (Borsboom et al., 2021; Eronen & Romeijn, 2020; Smaldino, 2017; Van Der Leeuw, 2004; in addition, a recent issue of *Perspectives on Psychological Science* was dedicated to this topic: Proulx & Morey, 2021). Rather than summarizing these publications, we offer a brief primer here.

Building a formal model entails *formalizing* ideas, that is, stating them in mathematical or logical terms. In the social sciences, theories are often verbal theories; they are phrased in natural language. Natural language is intuitive and allows us to concisely transmit large amounts of information. For instance, by describing behavior as "impulsive," a researcher can convey a range of different associations, prototypical behaviors, and consequences. However, natural language tends to be ambiguous, even if carefully crafted; some words have different connotations or interpretations, resulting in confusion. In contrast, a formal model is unambiguous. Describing ideas in explicit terms reduces conceptual confusion, facilitating communication between and within disciplines. The need for clarity is widely recognized. In 2015, an expert meeting of the *International Society for Research on Impulsivity* concluded that "progress in understanding and treating impulsivity is limited by a lack of precision and consistency in its definition, [leading to] inconsistencies across research domains and disciplines, slowing scientific progress" (Hamilton, Littlefield, et al., 2015, p. 168). Related, MacKillop et al. (2016) noted that "the use of a catch-all term impulsivity to refer to distinct characteristics may foster ambiguity and confusion in the literature" (p. 170). More broadly, Leising et al. (2021) emphasize that confusion over terminology hampers progress in the psychological sciences.

A formal *model* combines formalized ideas into an interrelated system of inputs, interactions, and outcomes. Formal models are similar to statistical models in that both serve to better understand variation in the real world and separate it from other factors. However, formal and statistical models tackle different problems and have different goals. A statistical model is designed to minimize the difference between empirical observations and the model's predictions. The goal is inference from a sample to a population. Formal models, in contrast, determine how the output of a system changes as a function of the inputs or features of that system. The goal is to clarify assumptions, explore consequences, determine the match between theory and data, or generate hypotheses for future research.

Although empirical observations inspire, constrain, and often validate formal models, such models do not necessarily need empirical observations as input. Instead, after a model is proposed, we can experimentally manipulate the input or assumptions and use the model to evaluate the consequences. This allows a modeler to explore a large range of parameters and possibilities. For instance, an impulsivity researcher may change one or several characteristics of an environment in the model (e.g., resource scarcity) and evaluate how these changes shape the costs and benefits of impulsivity. Such exploration does not replace empirical observation. But, it does provide theoretical insight and may inspire novel empirical predictions.

The Insights of Formal Models Have Not Been Integrated

Formal models studying how the environment shapes costs and benefits of impulsivity have been developed across the biological and social sciences, including psychology, biology, economics, sociology, and management. Despite their potential for integrative theory building, findings and insight from models from one discipline have had a limited impact on research in other disciplines. This lack of integration is problematic for modelers and empiricists alike. For modelers, this makes it difficult to build on the work of their peers. It may be that an open question for some is an answered question for others. By not speaking the same tongue, they run the risk of reinventing the wheel in different disciplines. For empiricists, it is difficult to see how modeling results may inform empirical studies. Impulsivity is important in a massive number of potential environments and decisions. This makes understanding what the costs and benefits of impulsivity are a massive puzzle. Each individual model studies only a handful of specific decisions in a limited number of simplified environments. As a result, they illuminate only a small piece of the puzzle at a time. This narrow focus makes it unclear how insights from a model can be translated to empirical hypotheses (Fenneman & Frankenhuis, 2020). Multiple models together can reveal general patterns and provide testable empirical hypotheses.

Building a Common Language to Integrate Formal Models

Our goal is to connect the dots by reviewing formal models of impulsivity and integrating their findings. Through this synthesis, we aim to understand in which environmental conditions impulsivity is adaptive, that is, when the benefits of impulsivity outweigh costs in the long term (Results section). Our approach is similar to meta-analyses of empirical studies, which integrate findings by expressing them on a similar scale (e.g., comparing standardized effect sizes). We first survey formal models from a range of disciplines exploring how environmental harshness and unpredictability influence the adaptiveness of temporal and information impulsivity. Based on this survey, we develop a conceptual framework that aligns different formal models on a similar scale, making it possible to compare the models. Our framework thus provides a "common language" (Method section). This framework provides an overview of the dimensions along which environments may differ, the actions available to an agent, and how variation in environments shapes the adaptive value of impulsive behaviors. Using this framework, we subsequently define inclusion criteria, harmonize results, and synthesize the findings of these models.

The Scope of Our Analysis

We focus the scope of our analysis in two ways. First, we study impulsive choice, that is, temporal and information impulsivity. We focus on impulsive choice because this topic is of long-standing general interest across the biological and social sciences. Our analysis does not include inattention or impulsive action, which are commonly studied in psychology, but less often in other disciplines. Second, we ask how environmental dimensions shape long-term costs and benefits of impulsive behaviors. That is, we ask *why* impulsive behaviors might be adaptive or maladaptive in the long term in different environmental conditions. This perspective is also known as an ultimate-level explanation (Tinbergen, 1963) or a computational level of analysis (Marr, 1982). Our analysis does not include *how* these behaviors are elicited by the environment or *how* cognitive systems give rise to impulsive behaviors (algorithmic-level analyses). Thus, our analysis focuses on formal models that study behavioral outcomes, without considering proximate-level mechanisms, such as neurobiological or cognitive processes. Ultimate and proximate levels of analysis are complementary, rather than mutually exclusive: Understanding how environments influence the costs and benefits of impulsive behaviors provides insights into how evolutionary and developmental processes shape neurobiological and cognitive systems. In the Limitations and Future Directions section, we discuss some limitations of models that focus on behavior without incorporating mechanism and offer recommendations for future directions to bridge models of behaviors and models of mechanisms.

Method

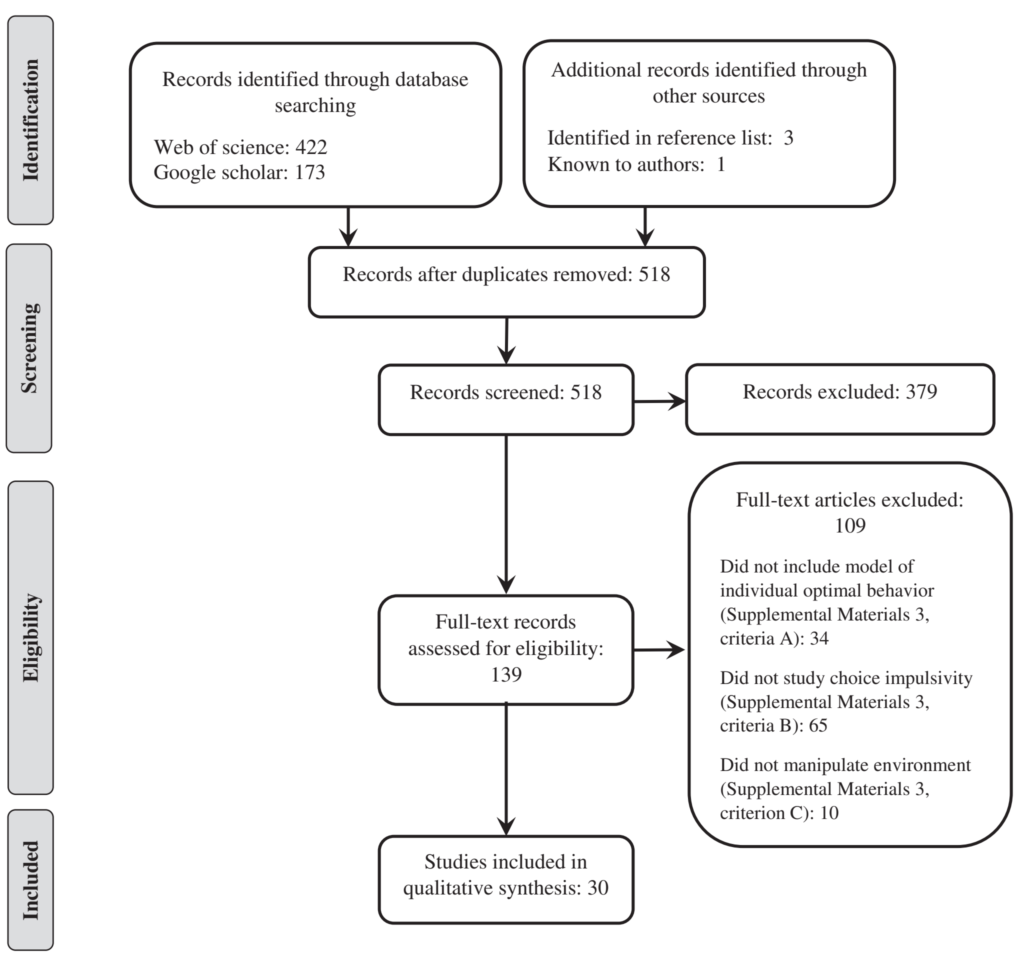
Our synthesis and integration of formal models consists of five steps. We started with a literature search for formal models of impulsivity (Step 1). Based on this search, we created a conceptual framework to serve as a "common language" (Step 2). This framework served as the basis for explicit conceptual definitions of information and temporal impulsivity, harshness, and unpredictability (Step 3). We used these definitions to determine which models study how harshness and unpredictability shape optimal levels of choice impulsivity and hence should be included in our qualitative assessment (Step 4). Finally, we standardized modeling results to be able to compare the findings of different models (Step 5). We discuss these steps in detail below.

Step 1: Preferred Reporting Items for Systematic Reviews and Meta-Analyses Literature Search

We used the Preferred Reporting Items for Systematic Reviews and Meta-Analyses protocol (Moher et al., 2009; Figure 1) as a guide for the process of reporting our systematic review on how the environment shapes the costs and benefits of impulsivity. We searched the Web of Science Core Collection database on and before March 13, 2018. Supplemental Material 2 lists which specific databases were included in this search.

Using Boolean logic and regular expressions, we constructed five sets of search keywords (Supplemental Material 2). The first three

Figure 1
Flow of Study Reports Into the Research Synthesis



sets contained keywords and synonyms related to impulsivity (Set 1), formal modeling (Set 2), and harshness and unpredictability (Set 3). This resulted in 1,411 publications. We reduced this set to 422 publications by applying a set of exclusion keywords (Set 4) and restricted our search to relevant academic disciplines (excluding, for instance, chemistry and physics; Set 5). In addition, we searched Google Scholar for references that included the keywords “impulsivity,” “environment,” “formal model,” or synonyms of these keywords, resulting in an additional 173 publications. We identified an additional three publications from the reference lists of these reports and one that was known to the authors.

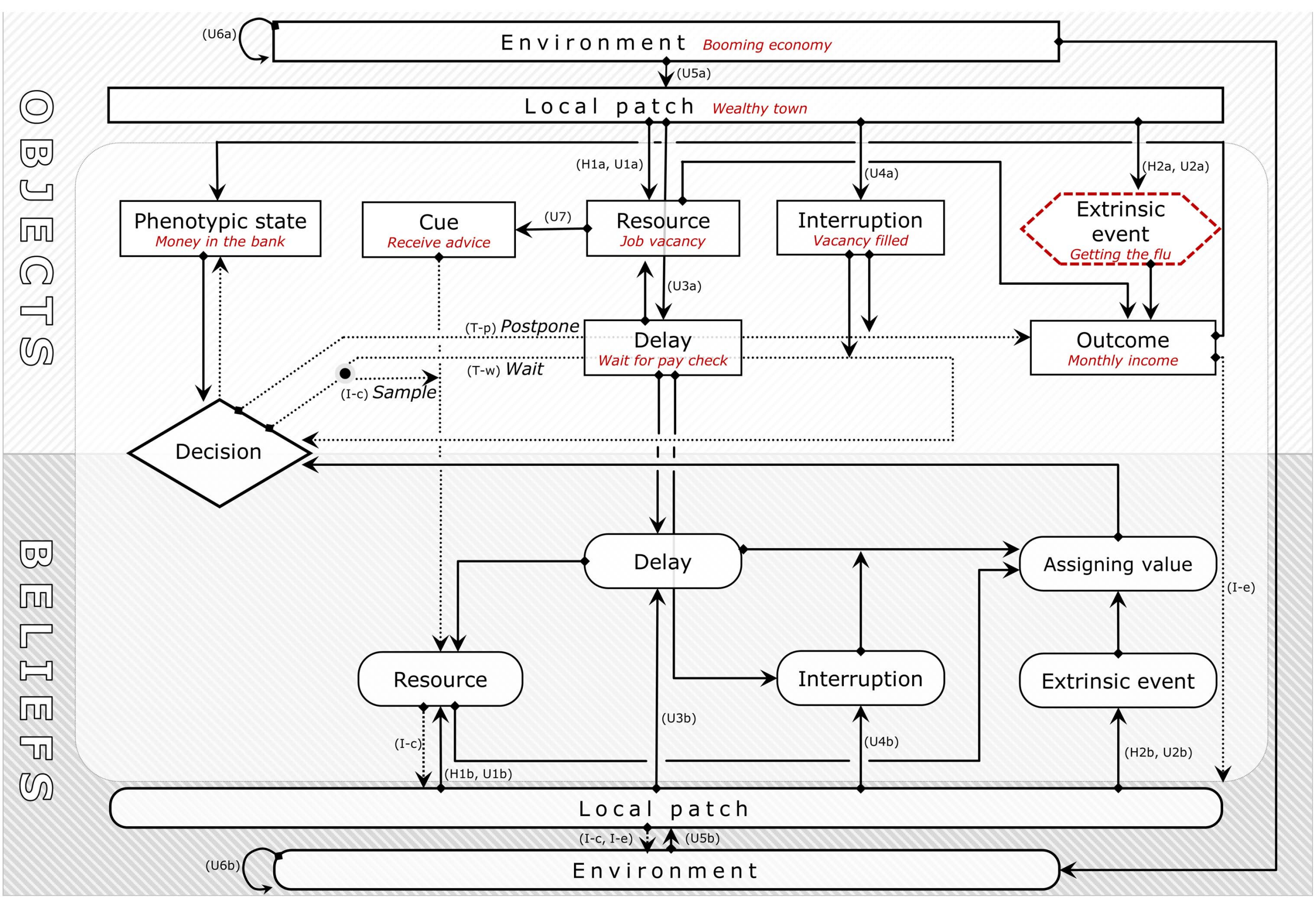
After removing duplicates, 518 unique reports remained. We screened the title and abstract of each of these references to assess whether the report describes a formal model that studies (a) the effects of environment on behavior, (b) optimal levels of impulsivity, or (c) both. A total of 138 reports passed this assessment. The first author then read all of these reports in full. Although we used all 138 reports to construct our conceptual framework, only 30 reports included a formal model that studied how environmental dimensions shape information and temporal impulsivity. Thus, our final synthesis includes only the 30 models from these reports.

Step 2: A Conceptual Framework as a Common Language

We developed our framework (Figure 2) based on analysis, interpretation, and discussion among the authors of these 138 models. Initially, we started with a broad conceptual framework capturing how “harshness” and “unpredictability” influence the costs and benefits of temporal and information impulsivity. After studying each model and (if necessary) discussing its content, we asked whether the current version of our framework captured the most important dynamics of this model. If the answer was “no,” we further asked which dynamics or nuances were missing (e.g., it might not differentiate between types of unpredictability) and updated the framework to incorporate these nuances (e.g., by explicitly specifying

Figure 2

The Conceptual Framework Guiding the Present Study



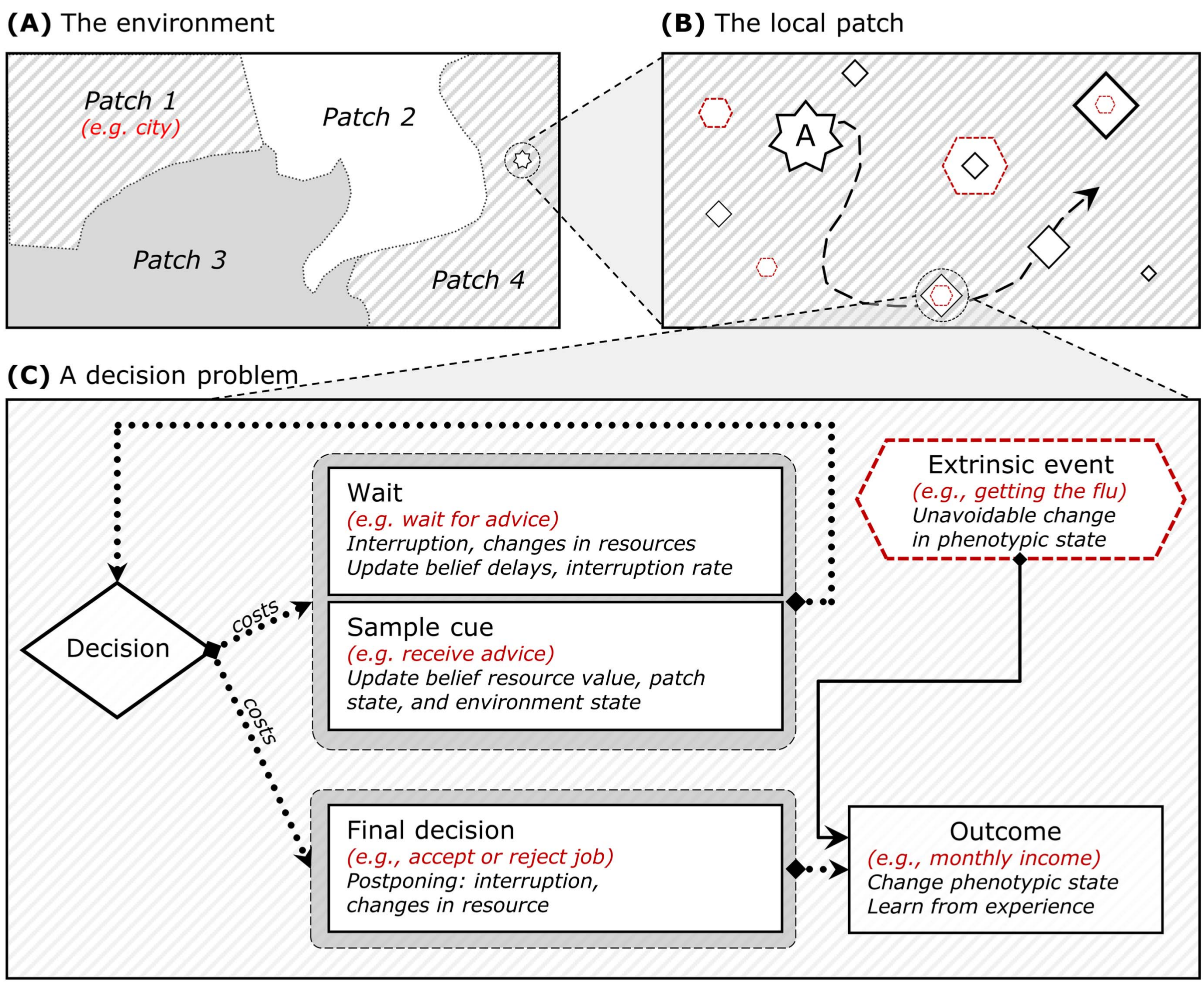
Note. Boxes indicate objects, entities that exist independently of the beliefs of an agent. There are seven types of objects: the phenotypic state; resources and cues about the quality of the resource; delays between an action and the outcome; interruptions that occur during a delay; the local environment or “patch”; the global environment; and the outcome of the decision problem. The red hexagon represents the extrinsic events that an agent cannot control. Round shapes represent an agent’s beliefs. Lines represent the flow of causality. Solid lines do not result from actions, but rather from the interactions between beliefs or objects. For instance, the environmental state influences the state of the local patch. Dotted lines represent the consequences of an action. Finally, the red text illustrates our running example. See the online article for the color version of this figure.

separate sources of unpredictability). We did not update our framework to incorporate all dynamics or nuances; our aim was to capture variation in environments and impulsive decisions between all *existing* models, not to perfectly describe all *possible* models. For this reason, our framework does not, for instance, include developmental processes or interactions with other agents (game theory).

The resulting conceptual framework describes a decision process in which many variables interact to shape outcomes. These variables fit into one of three categories: objects, beliefs, or relations. Below, we use a running example to define terms and explain these three categories. Figure 2 provides an in-depth view of the conceptual framework, where beliefs and objects interact to shape decisions. Figure 3 shows a simplified view of the decision problem from the perspective of an agent. This simplified figure shows the decisions an agent might encounter but omits beliefs that the agent may possess about these elements.

Our framework is broad: It covers many components and processes of decision-making. Individual models include some of these components and processes, but not all of them. In this sense, individual models are a special case of our general framework. To illustrate, consider two existing models of impulsivity. The first explores organizational beliefs and membership (March, 1991). The second explores how foraging animals explore their environment (Dall & Johnstone, 2002). At first, it may be difficult to see how these models are related. The similarities become clearer if we describe the models in abstract terms. For instance, both models incorporate similar environmental features (e.g., the environment of the company and the forager change over time) and include similar dynamics (e.g., beliefs become outdated if the environment changes). By expressing both models within our framework, we can see similarities in their structures and study which outcomes do, and do not, generalize across the models.

Figure 3
The Conceptual Framework From the Agent's Perspective



Note. An agent (represented with a hexagram labeled "A") moves around in its environment, which consists of multiple patches (Panel A). While it moves around in its current patch (Panel B), it repeatedly comes across resources (diamonds) or extrinsic events (red hexagon). When it encounters a resource (Panel C), it can repeatedly select a cue or wait, before postponing and making a final decision. These actions can have multiple consequences, described in italic text within each box. There are no actions when it encounters an extrinsic event. The red text illustrates our running example. See the online article for the color version of this figure.

Running Example

We use job search as a running example; however, our framework applies generally to decisions that feature trade-offs between sooner and later outcomes (i.e., temporal impulsivity), more or less uncertainty (i.e., information impulsivity), and where the costs and benefits depend on environmental conditions. Such decisions are widespread across all domains of life, including health, employment, and partner choice. For instance, we often face a decision between an active lifestyle promoting long-term health versus a hedonic lifestyle affording short-term pleasure. Or, we need to decide whether to study for an upcoming exam, which costs time and effort in the short term but might result in higher grades and less uncertainty in the longer term. Moreover, this decision structure is not limited to so-called contemporary Western, educated, industrial, rich, and democratic societies (Henrich et al., 2010); it also occurs in nonindustrialized, small-scale societies. For instance, members of pastoralist groups may need to decide whether to have their cattle graze in recently visited depleted pastures or visit more remote and uncertain pastures that might be more (or even less) productive. Visiting recently depleted pastures shows both temporal impulsivity (it avoids traveling time) and information impulsivity (it provides less information about alternative opportunities).

We use job search as our running example for two reasons: (a) a large number of people face the challenge of finding a job, often multiple times across the life course, across cultural and economic backgrounds and (b) whether people choose the right job may well have important long-term consequences for health, wealth, social relationships, and well-being. The psychology of job searching thus offers a recognizable exemplar for the analysis of the adaptive value of impulsive or nonimpulsive behavior, which ties together the different conditions we consider throughout this article.

In our example, a person repeatedly and sequentially encounters job vacancies. These jobs vary in quality: some are rewarding, safe, or interesting, whereas others are unrewarding, dangerous, or dull. A job seeker cannot directly observe the quality of each job, or whether this job suits them well. They can, however, gather information about this quality before deciding to apply. They might, for instance, consult a career advisor. While gathering information, the employer could hire someone else. If the job is still available, and they decide to apply, they may or may not be hired. Finally, they face extrinsic events: hardships that they cannot prevent, mitigate, avoid, or control. Such events are not related to the quality of a job but are imposed by external factors. For instance, their car might break down, reducing financial reserves.

The frequency and quality of jobs, the number of competitors, and the impact of extrinsic events depend on the community's economic condition. Some cities are generally safe and provide many opportunities for employment, while others are dangerous and offer fewer opportunities. Whether a city is safe or dangerous depends, in part, on the state of the economy, which may change over time; for instance, there may be fewer vacancies during a recession.

Phenotypes

An agent has a *phenotype*, a set of variables that describe its current state. In our example, a job seeker's phenotypic state consists of their financial reserves. Agents interact with objects, defined as entities in the environment, which influence their phenotypic state. In our framework, there are seven different types of objects.

Resources and Cues

The first of these seven types of objects are resources. Resources are objects that an agent makes a decision about. An agent does not control the quality of a resource. But, it can influence how the resource influences its phenotype by choosing whether to interact with the resource. For instance, although our job seeker cannot control the quality of a job, it can choose to apply for it or not.

An agent cannot directly observe the quality of a resource but can improve its estimate before making a decision by sampling imperfect cues. Sampling comes at a cost (e.g., time or energy spent sampling). Cues are observations that are more likely in certain conditions than others and therefore provide information on what the current condition is. How informative a cue is depends on the "cue reliability" (also known as the cue validity). If the cue reliability is high (e.g., good advice), a single cue nearly perfectly predicts the resource quality. If it is low (e.g., some job advice is solid, but other suggestions are ill-advised), sampling a cue barely reduces uncertainty. Although models differ in how they define and operationalize the reliability of cues, the common denominator is that cues provide probabilistic information about the state of an object. Although there might be cues in the real world that provide information about delays, interruptions, or extrinsic events, none of the models we analyzed included such cues. Rather, these models assumed that agents know the values of these events, as we discuss below. Consequently, our framework includes cues to the quality of resources, but not about other objects or events.

Delays, Waiting, Postponing, and Interruptions

Another types of objects are delays between actions and consequences. During a delay, a resource can increase or decrease in quality, or an interruption might occur. For instance, if there are many applications, an employer might change the criteria for hiring (e.g., raising the bar) or a vacancy may become unavailable if someone else is hired.

We distinguish between two types of delay: delays that follow a waiting action and delays that follow a postponing action (Fawcett et al., 2012; McGuire & Kable, 2013; Paglieri, 2013). Waiting is an action that can be repeated; choosing to wait does not end the current decision. While our job seeker is making the decision whether to accept a job offer, they continue to encounter new openings. At any time, the individual can stop this search by accepting a job. Postponing is a final action; it ends the current decision. An agent postpones if it makes a single decision between a sooner (typically smaller) or later (typically larger) outcome. When postponing, the entire delay (whether shorter or longer) is experienced in its entirety; there is no opportunity to revise a decision. After this delay, the decision process terminates. Suppose our job seeker finds a vacancy for a job that starts immediately, but knows that another position will open up soon. If so, the individual makes a single postponing decision, which cannot be changed afterward.

Extrinsic Events

Like resources, extrinsic events are objects whose value influences an agent's phenotype. Unlike resources, an agent has no control over how extrinsic events influence its phenotype. That is, the environment imposes costs or benefits on the agent, regardless of what an agent does. In our example, a job seeker has no control over whether their car breaks down, whether there is unprovoked violence, or whether they receive unsolicited financial or social support (e.g., an unexpected tax rebate). In extreme cases, extrinsic events can result in death (e.g., due to severe unprovoked violence or disease).

Local Patches

The quality of resources, the length of delay between resources, the likelihood of interruption, the reliability of cues, and the value of extrinsic events depend on an agent's local environment or "patch" (e.g., a city). There are different patches, which can be in different states. For instance, some cities are safe and offer many desirable jobs; others are dangerous and offer fewer jobs.

Global Environments

Finally, the state of the global environment shapes the state of all local patches in that environment. The state of the environment can change over time. In our running example, the environment reflects the national economy. Some years the economy is booming: Patches tend to be in good states; jobs are plentiful and high quality, the number of competitors for a job is low, and extrinsic events tend to be positive. Other years the economy is in recession: There are fewer desirable jobs, competition is fierce, and extrinsic events tend to be negative. In our terminology, an environment changes if at least one patch changes over time (e.g., a single city experiences economic decline). Moreover, some events change all patches simultaneously (e.g., economic recession at the national level). To be sure, different local patches can be in different states even if the global environment does not change. For instance, even if the economy does not change, some cities might be consistently richer than others.

Beliefs and Information

An agent does not always have full information about all objects in its environment when making a decision. Some objects cannot be directly observed but have to be inferred (e.g., the state of the economy). Other objects could be observed but have not yet been encountered (e.g., the quality of the next job opportunity). In some cases, those objects can be predicted based on an agent's beliefs (e.g., the likelihood that another person will fill a vacancy). The term "belief" here refers to estimates; it does not imply a conscious mental representation. Beliefs may be incorrect or incomplete, for instance, an agent might mistakenly believe the economy is faltering. Whenever an agent believes an object can have more than one possible value (e.g., jobs vary in quality), irrespective of whether this is true, there is *uncertainty*.

An agent uses three sources of information to form and update its beliefs. First, based on its evolutionary and/or developmental history, an agent may have a (learned or inherited) prior belief about the state of the environment, the local patch, and objects within that patch. In our example, a job seeker might, for instance, start out believing that economic recessions are rare. Second, after sampling a cue, an agent updates its belief about the resource's quality. This updating can scale up: By learning about a resource quality, an agent may also learn about the state of the local patch and thus learn about the quality of the overall environment. For example, if an agent receives only negative cues (e.g., all sampled jobs appear to have a low quality), it may become more pessimistic about the local patch's state (e.g., the city might be poorer than thought), in turn becoming more pessimistic about the environment (e.g., there might be a recession). Finally, an agent can learn from its experiences; the outcomes of some actions (e.g., accepting a job) provide information about the quality of a resource (e.g., it was a bad job).

Relations

Relations represent the flow of causality. Some relations are between objects. For instance, the state of the environment (e.g., the business cycle) influences the state of the local patch (e.g., wealth of a city), which in turn influences which resources, delays, interruptions, and extrinsic events exist (e.g., jobs and competition). Other relations are between beliefs. For instance, if an agent believes the environment (e.g., the job seeker's economy) is worsening, it might be pessimistic about the future of its local patch (e.g., its city). This belief about its local patch in turn influences which resources, delays, interruptions, risks, and extrinsic events it expects to encounter. Other relations are between objects and beliefs, such as when an agent explores actions it has not tried out previously to learn about objects.

Step 3: Defining Harshness, Unpredictability, and Impulsivity

Using the objects, beliefs, and relations of our conceptual framework, we formulate specific definitions of harshness, unpredictability, and impulsivity.

Harshness

We distinguish between two types of harshness: *resource scarcity* and *extrinsic harshness*. There are two ways in which a model can include resource scarcity. First, if there are two or more patches, or two or more possible states for a patch, where resources have a different mean quality or a different frequency (line H1a in Figure 2). That is, the model explores two levels of resource scarcity. Second, even if the mean quality or frequency is equal in all patches and all states, a model can include resource scarcity if an agent believes that at least two patches or states differ in their mean resource quality or frequency (line H1b). A patch is harsher than another patch if resources in the first patch are, on average, less frequent (e.g., there are few jobs) or have a lower mean quality (e.g., jobs pay poorly or can be dangerous). Similarly, there are two ways in which a model can include extrinsic harshness. First, there might be two or more patches, or two or more possible states for a patch, which differ in their mean value or in their mean frequency of extrinsic events (line H2a). Or, an agent might believe this to be the case, even when it is not true (line H2b). A patch is harsher here if extrinsic events have a lower mean value or negative extrinsic events are more frequent.

Unpredictability

We use the term "unpredictability" to refer to perceived or actual stochastic (i.e., random) variation in a dimension of the environment (for in-depth discussion of this definition, see Young et al., 2020).

That is, unpredictability implies that there is (perceived) variation in a dimension of the environment, which an individual cannot predict. We distinguish between seven different types of unpredictability:

- *Resource unpredictability:* There are at least two resources that differ in their quality (line U1a), or an agent believes that there are two resources that differ in their quality (line U1b).
- *Extrinsic unpredictability:* There are at least two extrinsic events that differ in their value (line U2a), or an agent believes that at least two extrinsic events differ in their value (line U2b).
- *Delay unpredictability:* There is at least one possible action that results in a delay with a duration that cannot be known with certainty (line U3a), or an agent believes that there is at least one action that results in an uncertainty delay (line U3b).
- *Interruption unpredictability:* There is at least one patch, or one state within a patch, where interruptions are neither absent nor guaranteed (line U4a), or an agent believes that there is at least one patch or one state within a patch, where interruptions are neither absent nor guaranteed (line U4b).
- *Spatial unpredictability:* There are at least two patches that are simultaneously in different states (line U5a), or an agent believes that at least two patches can be in different states (line U5b).
- *Temporal unpredictability:* The current state of the environment does not perfectly predict all future states of the environment (line U6a), or an agent believes that the current states does not predict the future states (line U6b).
- *Cue unpredictability* (the opposite of *cue reliability* or *cue validity*)*:* There are two or more patches, or two or more states within a patch, that differ in how reliable cues are (line U7).

Information Impulsivity

Information impulsivity is the tendency to act in such a way that an agent chooses to gather less information about the consequences of future actions than it could. This requires that there are at least two possible actions that an agent can take that differ in how much it learns about consequences. Besides its evolutionary and developmental history, there are two ways an agent can learn about consequences (see Beliefs and Information section above). First, it can sample cues (line I-c). For instance, a job seeker could look for advice before applying. Second, an agent can learn by sampling new experiences (line I-e). For instance, a job seeker accepting a job that turns out to be low quality may become more careful in future searches. When choosing between actions, an agent higher in information impulsivity takes an action that provides no (or fewer) cues or no (or less) informative experiences than an alternative action.

Temporal Impulsivity

Temporal impulsivity is the tendency to choose sooner rewards over later ones. This requires that there are at least two actions that an agent can choose from that differ in the (expected) delay duration. A model can study temporal impulsivity if an agent can wait (line T-w) or if an agent can postpone (line T-p; see also Delays, Waiting, and Postponing section). In a model of waiting, an agent can make at least one more decision to delay longer after the initial delay. In our example, the job seeker waits after sampling career advice. In a model of postponing, there are no further decisions to delay after the initial delay. An agent is higher in temporal impulsivity if it takes an action that results in shorter delays.

Step 4: Selecting Models for Synthesis

By restricting the value of objects and beliefs and eliminating relations, we can describe individual models as a special case of our framework. For instance, we can capture a model that does not include extrinsic events as one where extrinsic events always have a value of zero.

Based on the definitions from the previous sections, we created a checklist to determine whether a report in our literature search (a) includes a formal model; (b) explores temporal impulsivity, information impulsivity, both, or neither; and (c) explores what types of harsh or unpredictable environments, if any (Supplemental Material 3). We included a report in our review only if it included a formal model, studied at least one type of choice impulsivity (information or temporal), and studied at least one type of harshness or unpredictability.

Thirty out of the 138 reports passed these criteria (Table 1). One model was partially excluded due to a mathematical error in a central equation, which we have communicated to the authors. In our analysis, a model could capture impulsivity in two ways: by comparing different levels of impulsivity within a strategy (e.g., comparing more to fewer cues sampled) or between strategies (e.g., comparing agents that sample at least once vs. agents that never sample). If a model compared levels of impulsivity both within and between strategies, we annotated our results accordingly (Table 1). For example, Collins et al. (2006) compared both a nonimpulsive learning strategy to an impulsive fixed threshold strategy (Annotation A) and compared fixed threshold strategies that differed in how much information was sampled (Annotation B). This situation applied to three of the 30 models included in our analysis.

Step 5: Data Extraction and Analysis

Following the selection of models, we extracted the results from those 30 models that passed our inclusion criteria and standardized these results to enable comparison.

Extracting Results

To compare models, we present environmental dimensions and impulsivity on standardized scales. Whenever possible, we used quantitative results presented in tables or figures. If needed, these values were reverse-coded (multiplied with −1), so higher scores always indicated higher levels of harshness, unpredictability, and impulsivity. However, not all models reported exact values.

Some models described qualitative results, without exact numeric values. These models fall in one of two categories. Some models provided resulting equations, without providing numeric examples.

Table 1
An Overview of the Models Included in Our Review

No.	Authors (year)	Annotation	Discipline	Species studied	Cluster
1.	Campbell and Persaud (2008)	Resource scarcity manipulated as meal size (A) or meal probability (B)	Biology and psychology	Mice	—
2.	Chowdhry (2011)	—	Economics	Humans	—
3.	Collins et al. (2006)	Comparing either learning rule strategy versus a fixed threshold strategy (A) or strategies that use different fixed thresholds (B)	Biology	Mating animals	1
4.	Cresswell et al. (2007)	Assuming no (A), low (B), or high (B) spatial unpredictability	Biology	Penguins	2
5.	Cresswell et al. (2008)	—	Biology	Penguins	2
6.	Chu et al. (2010)	—	Economics and management	Humans	—
7.	Dall and Johnstone (2002)	—	Biology	Foraging animals	1
8.	Dubois et al. (2004)	Resource scarcity manipulated as high mate-to-chooser ratio (A) or high mate density (B)	Biology	Birds	—
9.	Fawcett and Johnstone (2003)	Results depend on whether desirable males are common (A) or rare (B)	Biology	Mating animals	1
10.	Fawcett et al. (2012)	Results depend on whether decisions are one-off (A) or repeated (D). If decisions are one-off, there can be no opportunity costs (B), or there can be opportunity costs (C). In some repeated decisions, an agent can wait rather than postpone (E)	Biology	Animals	1
11.	Fenneman and Frankenhuis (2020)	—	Psychology	Animals	3
12.	Frankenhuis and Panchanathan (2011)	—	Psychology	Developing animals	3
13.	Hall and Kramer (2008)	—	Biology	Foraging animals	—
14.	Hauser and Possingham (2008)	Manipulates temporal unpredictability by increasing the probability of random population collapse (A) or by making the recovery probability unknown (B)	Biology	Ecological systems managers	—
15.	Henly et al. (2008)	Results depend on whether the immediate (A) or delayed option (B) has a higher rate of gain	Biology	Foraging animals	4
16.	Henshaw (2018)	Manipulates resource scarcity by decreasing mate frequency (A) or quality (B)	Biology	Mating animals	—
17.	Hutchinson and Halupka (2004)	Results depend on whether the world is known (A) or has to be learned (B)	Biology	Mating animals	—
18.	Kokko and Mappes (2005)	—	Biology	Mating animals	—
19.	LiCalzi and Marchiori (2014)	—	Management	Organizations	6
20.	Luttbeg and Warner (1999)	Measures impulsivity as the best give-up-time (A) and by comparing a fixed constant give-up-time strategy versus an experience estimate (B)	Biology	Mating animals	5
21.	Luttbeg (1996)	—	Biology	Mating animals	5
22.	March (1991)	—	Management	Organizations	6
23.	Mathot and Dall (2013)	Sampling can be for survival (A) or for luxury (D). When sampling for survival, resources can be scarce (B) or abundant (C)	Biology	Foraging animals	1
24.	Mazalov et al. (1996)	—	Biology	Mating animals	—
25.	McGuire and Kable (2013)	—	Psychology	Humans	—
26.	Posen and Levinthal (2012)	—	Management	Organizations	6
27.	Santini et al. (2015)	*Partially excluded due to error*	Biology	Limpets	—
28.	Sherratt and Morand-Ferron (2018)	Manipulates resources scarcity by changing the benefits-to-cost ratio (A), resource frequency (B), or probability of a beneficial outcome (C)	Biology	Animals	—
29.	Stephens and Anderson (2001)	—	Biology	Animals	4
30.	Stephens et al. (2004)	—	Biology	Animals	4

This was true of five results in four models (Chowdhry, 2011; Chu et al., 2010; Fawcett & Johnstone, 2003; Fawcett et al., 2012). Others provided numeric examples, but only indirect comparisons. For instance, a model might study impulsivity in resource-scarce environments and in resource-plentiful environments, without directly comparing the two. This was true of seven results in four models (Fawcett & Johnstone, 2003; Fawcett et al., 2012; March, 1991; Mazalov et al., 1996). In both cases, we manually classified a result as either weakly, moderately, or strongly positive or negative, or as no effect. Which classification we used depended on the presented results and/or authors' description. In the absence of explicit comments by the authors, results were scored as either moderately positive or negative (e.g., if the authors stated that there is a positive or negative effect, without providing any other qualifiers). Alternatively, a result was scored as weakly positive or negative if the authors explicitly stated an effect was small (e.g., in "[Competition] *had little effect on the optimal rate of sampling* […]," Hall & Kramer, 2008, p. 1614). A result would have been scored as strongly positive or negative if authors explicitly noted a large difference in impulsive behaviors between environments.

However, no such relationships occurred in models that reported only qualitative results. Finally, a result was scored as no effect if authors' specifically indicated that there was (almost) no effect (e.g., "The [level of information impulsivity] therefore does not depend on the mean or variance of extrinsic events," Fenneman & Frankenhuis, 2020, p. 269). Importantly, omitting these classifications by describing all qualitative results as moderately positive, moderately negative, or as having no effect does not change the conclusions from our review.

Some models explored multiple variables that describe a single environmental dimension. For instance, some models manipulate the mean resource quality and frequency of resources independently. Values of both variables can meet our definition of resource scarcity. Other models explored interactions, manipulating one dimension while holding another constant at multiple levels (e.g., holding the level of resources in the environment constant while varying the level of danger of the environment). In both cases, we recorded each operationalization with a separate annotation (Table 1).

Standardizing Results

Because models operationalize impulsivity and environmental dimensions in different ways, it is not meaningful to compare exact numbers across models. For example, Luttbeg (1996) studies whether an animal should gather information about a potential mate's quality when the average mate quality is poor. Similarly, Posen and Levinthal (2012) study whether an organization should exploit existing knowledge or explore novel opportunities when future returns on investment are low. Although both study how resource harshness shapes the adaptive value of information impulsivity, the number of mate cues sampled and the organization's investment in exploration are not directly comparable. Despite an exact comparison, we can compare qualitative patterns. Specifically, if the level of harshness and unpredictability increases, does the optimal level of impulsivity increase, or decrease, or remain the same? To be able to make such comparisons, we standardized harshness, unpredictability, and impulsivity in each model. We express harshness, unpredictability, and impulsivity on a scale of 0–1, where 0 represents the lowest level in a model and 1 represents the highest level. Importantly, this rescaling did not change the relative impact of one dimension to other dimensions within the same model (i.e., the relative slopes remain the same). If a model included more than one measure of impulsivity (e.g., it might study both cues sampled and minutes waited), we separately standardized each measurement.

As an example, consider an agent that never samples when resources are perfectly predictable, but samples five cues when resources are unpredictable. Sampling more cues implies a lower level of information impulsivity; since five sampled cues is the highest amount in this example, it is standardized to the lowest impulsivity level, 0, while sampling no cues—the lowest amount in this example—is standardized to the highest impulsivity level, 1. On our standardized measure, this means that this agent scores 1 on impulsivity (no sampling) when the resource unpredictability is 0 (resources are perfectly predictable) and 0 on impulsivity (sampling 5 cues) when the resource unpredictability is 1 (resources are maximally unpredictable).

To make comparing patterns easier, we centered all effects. Specifically, we adjusted the intercept of each finding so that the total area under the curve was identical for all relations between impulsivity and harshness or unpredictability (i.e., 0.5). For instance, suppose two models both find that resource scarcity has a positive but weak effect on information impulsivity (e.g., in this case, the slope is 0.05). These two models differ in the absolute levels of impulsivity (the intercept). In the first model, agents living in an environment where resources are relatively plentiful have an impulsivity score of 0.7, whereas in the second model, they have a score of 0.4. This makes it more difficult to directly compare environmental influences on impulsivity (the slopes). In contrast, after centering, these lines are equal. For instance, if the slope of both effects is 0.05, their intercept was set to 0.45 so that the area under the curve was 0.5 for both.

Transparency and Openness

All materials and data used in this review are available online. Supplemental Materials 2 and 3 provide an overview of the search terms we used and provide all the inclusion and exclusion criteria we used. The data extracted from the 30 models we included, as well as all scripts used for data entry, data processing, and creating figures, are available at https://osf.io/m2fp6. Additionally, we provide an overview of how the data were extracted for each model and, if applicable, why and how qualitative patterns were transformed to quantitative descriptions (e.g., moderate or weakly positive). This study was not preregistered.

Results

Description of Included Models and Patterns

Of the included 30 models, four models were published before the year 2000, 15 were published between the years 2000 and 2010, and 11 were published after 2010 (Figures S4.1 and S4.2 provide a graphical overview). The majority of included models were published in a biology journal (21, of which 11 study foraging behavior and nine study mating behavior). In addition, two models were published in economic journals, three in management journals, and three in psychology journals. In total, 17 reports share overlapping authors, clustered within five networks (Table 1). One author contributed to three reports (Table 1, Cluster 4). Six authors contributed to two reports (Table 1, Clusters 1, 2, 3, and 5). The remaining 13 reports do not share overlapping authors. Finally, there was one other cluster of reports (Table 1, Cluster 6): Posen and Levinthal (2012) critiqued and extend the model by March (1991), and subsequently, LiCalzi and Marchiori (2014) critiqued and extend the model by Posen and Levinthal (2012). Finally, three out of the 30 reports included both a formal model and a quantitative empirical test derived from that model. Two reports study animal behavior (Henly et al., 2008; Stephens & Anderson, 2001), and one studies human decision-making (McGuire & Kable, 2013).

The 30 models we selected for analysis included 94 patterns concerning how the environment shapes information and temporal impulsivity. Of these 94 patterns, 49 study information impulsivity and 45 study temporal impulsivity. Supplemental Material 4 provides an overview of which model studies which environmental dimension and which type of impulsivity. Here, we order these patterns by impulsivity type and environmental dimension. We first discuss how resource scarcity and unpredictability shape information impulsivity. Then we discuss how resource scarcity and unpredictability shape temporal impulsivity. Next, we discuss interruptions and extrinsic events, which have similar effects on both types of impulsivity. Figure 4 provides a graphical abstract of our results.

How Resource Scarcity Shapes Information Impulsivity

How resource scarcity shapes information impulsivity depends on how an agent gathers information. In some models, an agent can sample cues that provide information about possible consequences (Figure 5, results marked "C"). In other models, an agent gathers information by taking actions and then experiencing their consequences (Figure 5, results marked "E"). As shown in the panels in Figure 5, when resources are scarce, sampling cues is adaptive, whereas sampling experiences is maladaptive. This difference seems to result from the much greater costs involved in sampling experiences than sampling cues. We discuss each separately.

When Sampling Cues

We found four results in four models that explore how resource scarcity shapes optimal sampling of cues (Figure 5, results marked "C": #9, #11, #13, and #21).[1] Three results (#9, #11, and #21) show that, when sampling cues, information impulsivity is adaptive in resource-affluent environments, and maladaptive in resource-scarce environments. The other model (#13) shows no effect of resource scarcity. The costs of sampling are paid upfront before the resource affects an agent's phenotype. That is, these costs do not depend on the outcome of a decision. For instance, the costs of soliciting advice before accepting a vacancy do not change when the job turns out to be a good or bad fit.

When resource scarcity is low, most resources have a high quality, and selecting a random option likely results in a good outcome (e.g., most jobs have a good wage). Sampling cues still improves an agent's estimate (e.g., what the exact quality of a job is). But, the marginal increase in accuracy is low and is unlikely to produce benefits that outweigh costs of sampling. An impulsive agent saves sampling costs without decreasing its outcomes by much.

When resource scarcity is high, the mean resource quality is closer to zero. If there is at least some resource unpredictability, selecting a random option can result in good (e.g., jobs pay well) or bad outcomes (e.g., jobs pay poorly). Sampling cues enables an agent to better distinguish between good and bad options, favoring less information impulsivity.

Finally, Fenneman and Frankenhuis (2020, [#11]) study extreme scarcity, when almost all resources are bad. Here, information impulsivity is adaptive again. In this situation, an agent should err on the side of caution by rejecting all but the most promising resources. Sampling cues about a resource that is likely to be rejected anyway is costly, and it offers very little potential benefit.

When Sampling Experiences

We found 11 results in seven models that explore how resource scarcity shapes experience sampling (Figure 5, results marked "E": #7, #8A, #8B, #20B, #23A, #23D, #24, #26, #28A, #28B, and #28C). Ten results show that, when sampling experiences, information impulsivity tends to be maladaptive when resources are affluent and tends to be adaptive when resources are scarce (#7, #8A, #8B, #20B, #23A, #23D, #26, #28A, #28B, and #28C show this pattern; #24 does not). When resources are scarce, sampling experiences becomes more costly, increasing the adaptive value of information impulsivity. There are at least two types of costs to sampling experiences. First, experiencing negative resources results in a worse phenotype. For instance, working a dangerous job may result in workplace injuries. Second, there are *opportunity costs*: While exploring novel experiences, an agent cannot at the same time exploit an action known to be rewarding (Sherratt & Morand-Ferron, 2018, [#28]).

When resource scarcity is low, sampling experiences has low costs. The reason depends on whether scarcity is low because resources are frequent (results marked with a subscript "f": #7, #8A, #8B, #20B, and #28B) or because resources have a high mean quality (results marked with a subscript "m": #13, #23A, #23D, #24, #26, #28A, and #28C). If resource scarcity is low because resources are frequent, missing out on a single good opportunity can be compensated by many future encounters (e.g., there are many jobs). Moreover, when resources are frequent, sampling experiences is especially beneficial as new information can be used in many future encounters. If resources are plentiful because the mean resource quality is high (e.g., most jobs are good), sampling a new experience can still result in a bad outcome (e.g., some jobs are bad). However, negative experiences are unlikely to be very bad, making the potential cost of sampling experiences small. These low costs of sampling experiences increase the adaptive value of sampling and decrease the adaptive value of information impulsivity.

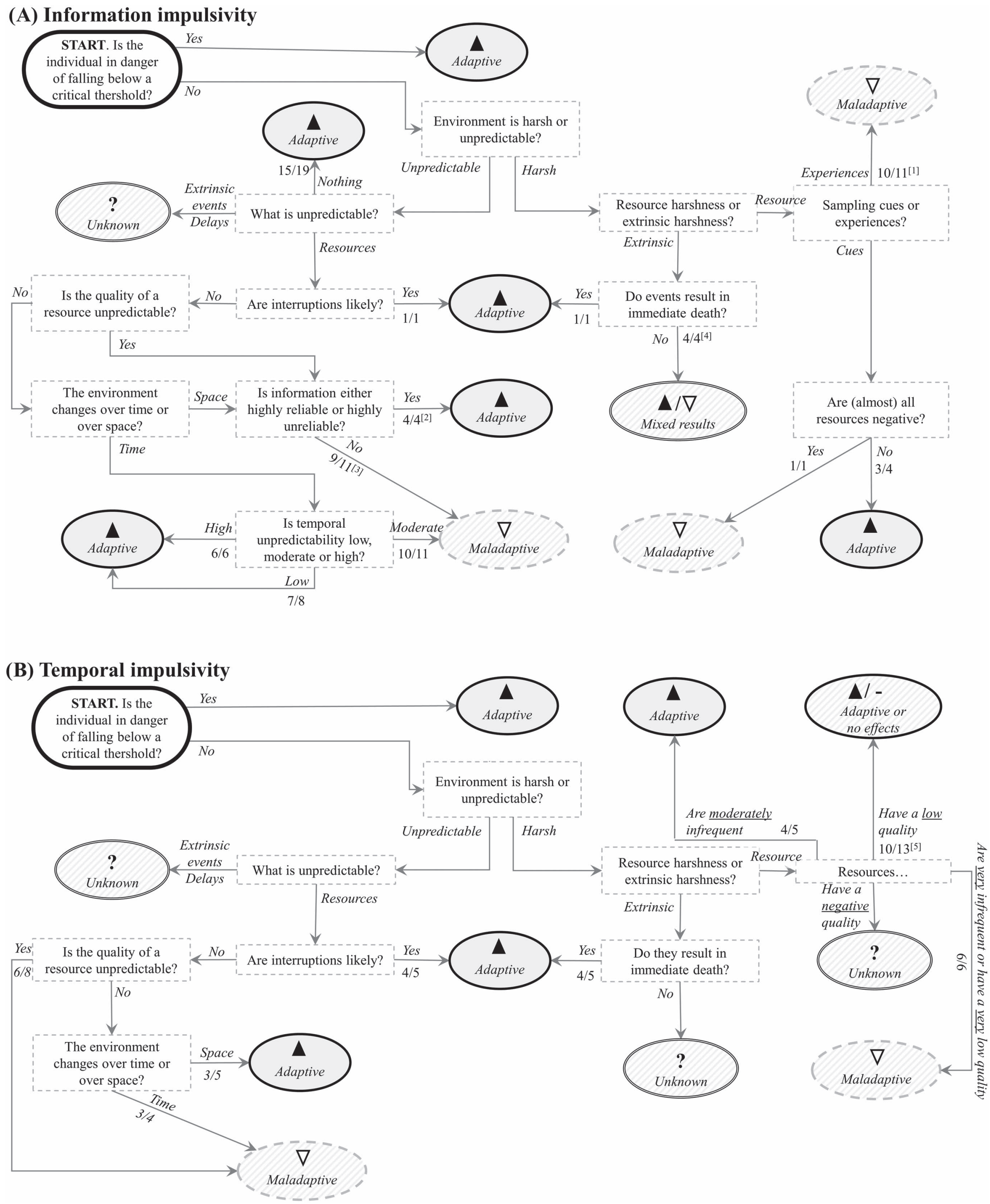
When resources are scarce, information impulsivity is adaptive. When resources are scarce because they are infrequent, information gained from sampling new experiences cannot be used in many future decisions. As such, sampling provides little benefit, yet prevents an agent from taking the action it believes will result in the best outcomes. When resources are scarce because they have a low or negative mean quality, sampling a new experience is likely to turn out to be disappointing or even dangerous. To make matters worse, an agent growing up in scarcity is likely to have a poorer phenotypic state (e.g., living in poverty causes wear and tear on the body). Any potential damage by sampling a wrong experience might be especially harmful as it could push an agent's phenotypic state below a *critical threshold*. A critical threshold is a minimum level of reserves that an agent needs to function. Falling below this threshold severely reduces health (or well-being, wealth, fitness, etc.). These decreases can be very costly or even impossible to reverse. For example, the sale of a foreclosed house typically results in a lower gain than that house is worth. Thus, a small deficit in money might cause large setbacks in net wealth, and these losses are not easily recouped. Other thresholds are more extreme: Death due to starvation cannot be overcome by more food (Mathot & Dall, 2013, [#23A and #23D]). In such cases of resource scarcity, sampling experiences can be very costly, so information impulsivity is likely to be even more adaptive.

The results discussed above are only true if sampling is costly. If there are no costs, an agent keeps sampling experiences until it has obtained a good resource, relative to the available resources in the environment (this scenario is known as the *secretary problem*;

[1] Here and in the following text, these numbers refer to the list of models in Table 1.

Figure 4

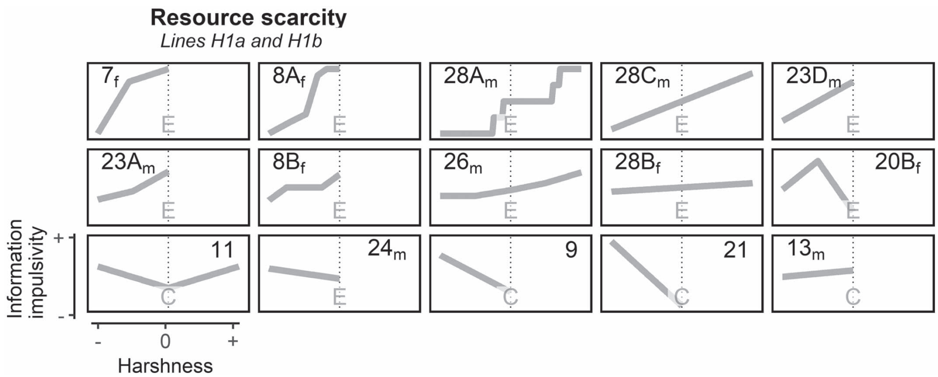
A Visual Depiction of the Present Study's Findings



Note. Starting from the top-left box, this flowchart provides a rough overview of the main patterns in our review. Arrows annotated with a fraction indicate how many patterns (numerator) out of the total number of patterns (denominator) show this effect.

[1] Five out of five patterns that study scarcity due to a low resource frequency and five out of six patterns that study scarcity due to a low or negative mean resource quality show this result. [2] These models study cue sampling, not experience sampling. However, we expect the same results for experience sampling. [3] Two out of three patterns on spatial unpredictability and seven out of eight patterns of resource unpredictability show this result. [4] Two patterns suggest that information impulsivity is adaptive, and two suggest there is no effect. [5] There is no effect on temporal impulsivity if all outcomes have a low quality. Temporal impulsivity is adaptive if only later outcomes have a low quality.

Figure 5
How Resource Scarcity Shapes Information Impulsivity



Note. Each panel represents one formal modeling result. Table 1 indicates which model corresponds to each number or number–letter pair. Panels are ordered by slope, starting with monotonic positive slopes, followed by slopes that can be positive or negative, followed by monotonic negative slopes, and finishing with (almost) flat slopes. Results from models that study cue sampling are marked with "C," whereas models that study experience sampling are marked with "E." Some models of experience sampling study resource harshness as a low frequency of resources (marked with a subscript "f"), whereas others study resources harshness as a low mean resource quality (marked with a subscript "m"). The *x*-axis shows the degree of environmental harshness, and ranges from environments where resources have a positive mean quality ("−") to environments where resources have a mean quality around zero ("0") to environments where resources have a negative mean quality ("+"). Models that do not study this whole range are represented with lines that either stop or start at the "0" point. The *y*-axis shows what level of information impulsivity is adaptive, ranging from low ("−") to high ("+").

Mazalov et al., 1996, [#24]). Moreover, the time it takes to find a resource that has a high quality relative to all other resources in the environment (e.g., a job with a salary in the top 10% income bracket) does not depend on the mean resource quality. As a consequence, there are no effects of resource scarcity when sampling experiences is cost-free.

How Unpredictability Shapes Information Impulsivity

We found 22 results in 15 models that explore how resource, spatial, or temporal unpredictability shape information impulsivity (Figure 6, Panel A: #3A, #7, #8, #11, #13, #21, #24, and #28; Panel B: #3A, #12, and #17B; and Panel C: #3A, #7, #13, #14A, #14B, #17B, #19, #20B, #22, #24, and #26). When there is little to no resource, temporal, or spatial unpredictability, information impulsivity is often adaptive (15 out of 19 results in Panels A, B, and C in Figure 6 that include low levels of resource, temporal, or spatial unpredictability show this pattern).

In highly predictable environments, there are two possibilities. First, all resources have a similar quality over space and time (e.g., jobs provide similar wages in all cities). If so, actions result in similar outcomes. Impulsivity is adaptive here because it saves on sampling costs. Second, resources do differ in quality over time and space, but an agent has detailed prior knowledge about the quality of resources, reducing its uncertainty (e.g., jobs offer different wages, but wages are known in advance). If so, the marginal benefit of more information is small. Nonetheless, in real-world decision problems, there is almost always appreciable unpredictability. How this unpredictability shapes whether information impulsivity is good or bad will depend on whether the environment is stable over time (there is spatial or resource unpredictability, but no temporal unpredictability) or unstable (there is temporal unpredictability). We discuss each in turn.

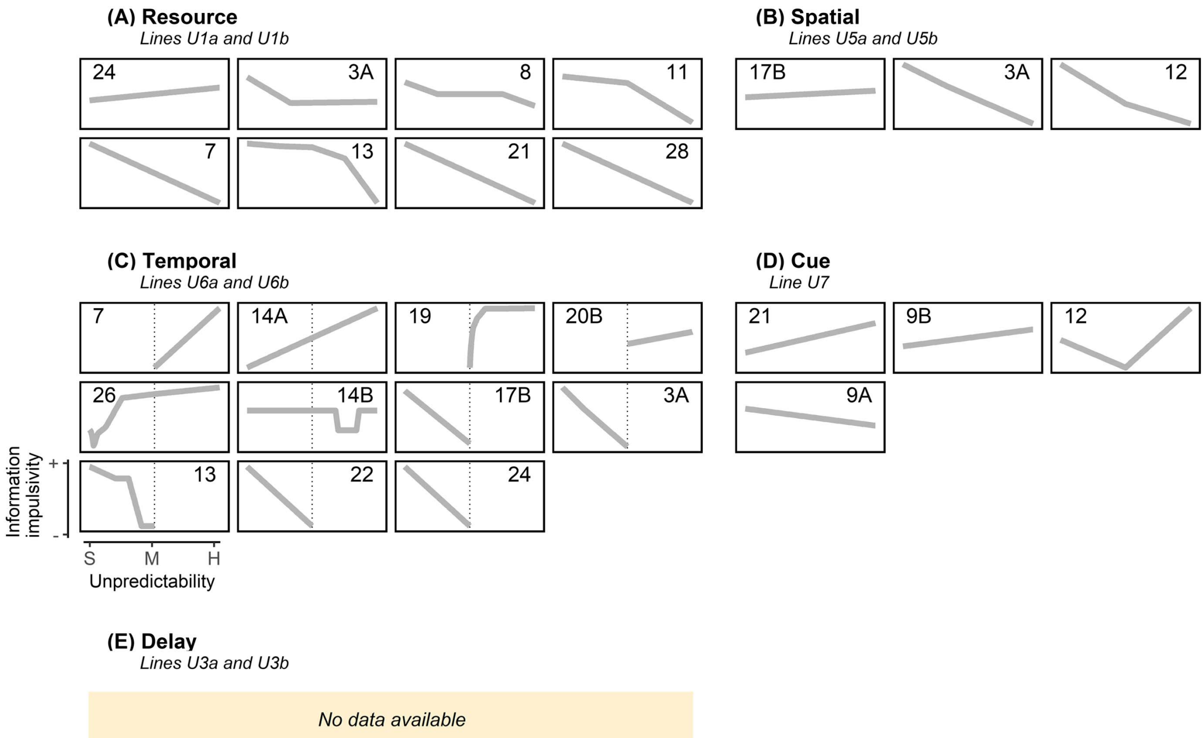
Information Impulsivity in an Unpredictable but Temporally Stable Environment

We found 11 results in 10 models that explore how resource and spatial unpredictability shape information impulsivity (Figure 6, Panels A and B). Nine results show that information impulsivity is maladaptive in resource or spatially unpredictable environments (Figure 6, Panel A: #3A, #7, #8, #11, #13, #21, and #28 show this pattern, #24 shows the opposite effect; Panel B: #12 and #3A show this pattern, #17B shows the opposite effect). When resources are unpredictable, they can be good or bad, making information sampling adaptive. This result also holds when the environment is spatially unpredictable. In both cases, an agent is uncertain about the consequences of its actions (e.g., whether accepting a job is good). By sampling information, the agent tends to increase the accuracy of its beliefs, enabling it to select better actions.

There are two exceptions to this pattern. First, Mazalov et al. (1996, [#24]) found that when searching for mates, a nonimpulsive strategy that samples information outperforms an impulsive strategy when resources are unpredictable. Thus, information impulsivity may be adaptive in resource-unpredictable environments. But, the difference between the two strategies is small. Second, Hutchinson and Halupka (2004, [#17B]) found that information impulsivity is adaptive when there is spatial unpredictability, opposite to the other models. However, their model holds the total amount of unpredictability constant; an environment higher in spatial unpredictability had lower resource unpredictability and vice versa. Consequently, there could be two reasons why information impulsivity is adaptive

Figure 6

How Unpredictability Shapes Information Impulsivity



Note. Each panel represents one formal modeling result. Table 1 indicates which model corresponds to each number or number–letter pair. Panels are ordered by slope, starting with monotonic positive slopes, followed by slopes that can be positive or negative, followed by monotonic negative slopes, and finishing with (almost) flat slopes. The *x*-axis shows the degree of environmental unpredictability. In Panel C, the temporal unpredictability ranges from environments that are stable over time (“S”) to environments that are moderately temporally unpredictable and change several times per lifetime (“M”) to environments that might change after every decision (“H”). The *y*-axis shows what level of information impulsivity is adaptive, ranging from low (“−”) to high (“+”). See the online article for the color version of this figure.

in spatially unpredictable environments. First, spatial unpredictability directly increases the adaptive value of information impulsivity. Second, spatial unpredictability actually decreases the adaptive value of being informationally impulsive (sampling few or no cues), but this effect is overshadowed by a decrease in resource unpredictability. This explanation is possible if resource unpredictability has a stronger effect on the adaptiveness of information impulsivity than spatial unpredictability. If so, higher spatial unpredictability might make information impulsivity appears to be maladaptive in their model, but this result is due to a decrease in resource unpredictability.

An agent should not always sample when there is resource or spatial unpredictability. Rather, whether an agent should sample or not depends on the reliability of cues and the benefits of having increased accuracy. We found four results in three models that study cue reliability (Figure 6, Panel D: #9A, #9B, #12, and #21). All four suggest that when cues are quite unreliable, each cue provides little information (e.g., a single bankruptcy provides little insight into the current state of the local economy). An agent needs many cues to substantially increase the accuracy of its beliefs, the cost of which may not be worth it. As a result, information impulsivity is adaptive when cues are unreliable (#12, #21). Sampling costs are especially likely to outweigh benefits when the resource quality is low (#9B). When jobs pay poorly, seeking expensive advice is ill-advised. An agent should sample multiple cues of low reliability only when high-quality resources are very common (e.g., some jobs pay very well; #9A).

Likewise, when cues are highly reliable (e.g., housing prices strongly predict levels of neighborhood crime), sampling only a few cues already produces an accurate estimate. After a few cues, the marginal knowledge gained from sampling additional cues is small, so impulsivity is adaptive (#12). In between these extremes is a goldilocks zone: When cues are moderately reliable, sampling several cues increases accuracy without being too expensive (e.g., when some job advice is solid but other suggestions are ill-advised, it is best to rely on multiple sources). Note that these models explore only cue and not experience sampling. Nonetheless, we expect the same pattern to arise when agents sample unreliable experiences, but future research could explore this question.

Information Impulsivity in a Temporally Unstable Environment

We found 11 results in 10 models that explore how temporal unpredictability shapes information impulsivity (Figure 6, Panel C:

#3A, #7, #13, #14A, #14B, #17B, #19, #20B, #22, #24, and #26). Together, these 10 results show that temporal unpredictability shapes the usefulness of information impulsivity in a U-shaped pattern: Information impulsivity is adaptive for a temporally stable (predictable) environment, maladaptive for a moderately unstable (semipredictable) environment, and adaptive again for a very unstable (i.e., rapidly changing and unpredictable) environment (#14B and #26 show a U-shaped pattern over the full range of temporal unpredictability; #3A, #13, #17B, #22, and #24 show a decrease for low levels of temporal unpredictability; #7, #19, and #20B show an increase for high levels of temporal unpredictability).

If the environment is temporally stable, information impulsivity is maladaptive early in life, but adaptive afterward. In temporally stable environments, knowledge accumulates—each cue or experience helps an agent to estimate the current and future states of the environment. Yet, information gained earlier is more valuable than information gained later because information gained sooner is useful in more decisions. As such, in temporally stable environments, an agent should focus on gathering information early on. After this initial sampling, it should then stop sampling for the rest of its life (#12, #14; for a comparable empirical result, see Sang et al., 2020). For instance, when growing up in an environment where resources are consistently poor, an agent may learn that its environment is stable. Accordingly, it should adjust its standards (e.g., accept job offers with low wages), rather than search for better options. Hence, information impulsivity is adaptive at the lowest levels of temporal unpredictability (i.e., stability).

When there is moderate temporal unpredictability, information impulsivity is maladaptive. When an environment changes, an agent's knowledge becomes outdated. The more common or extreme changes are, the faster information becomes outdated. If changes are infrequent (e.g., there is an economic recession every decade or so), information gained now is relevant for some time. Consequently, in this situation, an agent should continue sampling throughout its life to keep its beliefs in line with the state of the environment. Not keeping beliefs in line with reality comes with two major costs. Consider an impulsive agent that does not sample cues or experiences, but rather relies on what it already knows about the mean resource quality in its environment (e.g., it believes well-paying jobs are common). If the state of the environment deteriorates, this agent invests time and reserves to search for resources that no longer exist or are increasingly rare (an "oversampling error": Dunlap & Stephens, 2012; Dunlap et al., 2017). For instance, in an economic depression, searching for great jobs costs time and energy, yet is unlikely to pay off. Second, if the state of the environment improves, an impulsive agent is not able to capitalize on this change by increasing its standards (an "overrun error": Dunlap & Stephens, 2012; Dunlap et al., 2017). For instance, when the economy booms, an agent would miss out on better jobs that were not previously available. As a consequence, information impulsivity is less adaptive when temporal unpredictability is moderate.

When there is high temporal unpredictability, the environment might change after every decision (e.g., job availability changing from day to day). Any information gained about the current state of the environment will quickly become outdated, reducing the benefit of sampling. Moreover, an agent can do little if the environmental state changes for the worse (e.g., economic recession). Rather than investing in improving its estimates, an agent should invest in building phenotypic reserves. In this scenario, it is adaptive for agents to be impulsive if this allows them to save on costs and build up reserves. For instance, when the economy is very unstable, a job seeker's priority is to make ends meet in the short term. Rather than searching for a well-paying job, an agent should take the first job that pays well enough. In that sense, extreme temporal unpredictability has a similar effect on optimal behavior: Agents should sample little, that is, be informationally impulsive.

How Resource Scarcity Shapes Temporal Impulsivity

We found 18 results in 11 models that explore how resource scarcity shapes temporal impulsivity (Figure 7; #1A, #1B, #4A, #4B, #4C, #5, #8A, #8B, #10B, #10C, #10D, #13, #16A, #16B, #17A, #20A, #27, and #29). Thirteen results show that resource scarcity has an inverted U-shaped effect: Temporal impulsivity is adaptive in environments where resources are moderately scarce, but it is maladaptive when resources are plentiful or very scarce (#1A, #1B, #4A, #4C, #5, #8A, #8B, #10D, #16B, #17, #20A, #27, and #29 show this pattern; #4B, #10C, and #16A show monotonically decreasing effects; and #13 and #10B show no effect). Interestingly, no model studied negative resource qualities; in all models, resources always were either absent (i.e., a quality of 0) or positive. Whether an agent should be temporally impulsive depends, broadly speaking, on four factors: an agent's phenotypic state whether options are mutually exclusive, how often decisions are made, the rate of gain of each option, and the phenotypic state of an agent.

If an agent's phenotypic state is close to a critical threshold, it should impulsively prefer sooner rewards over later ones (#1A, #1B, #4A, and #4C; see also How Resource Harshness Shapes Information Impulsivity section). After all, future resources are worthless if an agent is not alive to take possession and use them. Or less extreme, when facing foreclosure, a job seeker should prioritize immediate income, even they might encounter a better job at some point in the future.

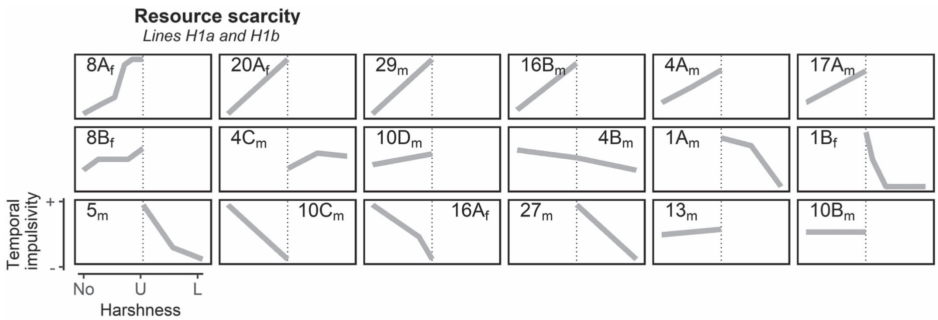
If options are mutually exclusive, there are opportunity costs: A delay implies forgoing other rewarding options (see also How Resource Harshness Shapes Information Impulsivity section). For instance, people can often hold only one full-time job at a time. If alternative options are more rewarding than delaying, an agent should terminate the current encounter as soon as it can, regardless of whether a decision is one-shot or repeated (#10B, #10C; opportunity costs are discussed, but not manipulated in Stephens & Anderson, 2001, [#29]).

If a decision is made once (or very rarely, e.g., selecting a long-term job), an agent should opt for the reward that maximizes lifetime outcomes, regardless of how much it needs to delay (assuming that there are no interruptions as discussed below; #8A, #8B, #10B, #13, and #16B). For example, if a short-term available income substantially improves the job seeker's quality of life by providing the funds needed for a much-needed car repair, it is better to take the first job available. In contrast, if the job seeker can afford to wait for a better job that provides the funds needed to buy a better car, it is better to delay.

If a decision is made repeatedly (e.g., jobs are temporary), whether an agent should delay depends on the *rate of gain*, defined as the average expected benefit of an outcome, divided by the duration of the delay (#10D, #29). This duration consists of the time spent waiting for an outcome (e.g., the time between accepting a job

Figure 7

How Resource Scarcity Shapes Temporal Impulsivity



Note. Each panel represents one formal modeling result. Table 1 indicates which model corresponds to each number or number–letter pair. Panels are ordered by slope, starting with monotonic positive slopes, followed by slopes that can be positive or negative, followed by monotonic negative slopes, and finishing with (almost) flat slopes. Some study resource harshness as a low frequency of resources (marked with a subscript "f"), whereas others study resource harshness as a low mean resource quality (marked with a subscript "m"). The *x*-axis shows the degree of environmental harshness, and ranges from environments where starvation is not possible ("no") to environments where starvation is unlikely ("U") to environments where starvation is likely ("L"). The *y*-axis shows what level of temporal impulsivity is adaptive, ranging from low ("−") to high ("+").

and the first paycheck), as well as the time between resource encounters. Note that this rate is high either when the expected benefit is high or the delay is short.

When resources are plentiful, temporal impulsivity is often maladaptive, as seen in nine out of the 14 results in Figure 7 where starvation is not possible (#4A, #8A, #8B, #10D, #16A, #16B, #17A, #20A, and #29 show this result; #10C and #16A show the opposite result; and #4B, #10B, and #13 show no result). Why temporal impulsivity is maladaptive depends on whether resources are frequent (results marked with subscript "f") or have a high mean quality (results marked with subscript "m"). When resources are frequent, the delay to the next (and possibly better) resource is typically short. This increases the rate of gain of delaying, making temporal impulsivity maladaptive. For instance, when jobs are common, searching for a better alternative takes less time, and so impulsivity is not adaptive. When the mean resource quality is high, waiting often results in larger outcomes, thus also increasing the rate of gain (#10D, #17A, #29). In contrast, when resources are plentiful, it is also possible that there could be better alternatives than to delay, if there are substantial opportunity costs. For instance, rather than spending unpaid time searching for a job, a job seeker might earn some income with day labor. Here, temporal impulsivity is adaptive if the opportunity costs of delaying are higher than the rate of gain of delaying, but maladaptive otherwise.

When resources are moderately scarce, temporal impulsivity is adaptive. When resources are scarce because they are infrequent (results marked with subscript "f"), an agent needs to wait longer for better options. Doing so reduces the rate of gain of delaying, making temporal impulsivity adaptive. Resource scarcity due to a low mean quality (results marked with subscript "m") can influence temporal impulsivity in two ways. First, temporal impulsivity can be adaptive if when resources are scarce, if resource scarcity means that future resources have a low quality. If there are no great jobs to wait for, an individual is better off by impulsively accepting the first job. However, there is no effect if all resources are devalued in equal proportion. If so, the absolute benefit of waiting decreases, but the rate of gain of waiting relative to that of acting impulsively remains the same. For instance, if all wages are reduced by an identical percentage, monthly incomes are lower, but this does not change how much better a future job is relative to a currently available one. Second, temporal impulsivity is adaptive when resource scarcity means that an agent cannot build meaningful phenotypic reserves. For instance, if jobs pay poorly, our job seeker might live from paycheck to paycheck, making it more likely to fall below some critical threshold. Here, temporal impulsivity provides immediate resources that keep the agent from falling below a critical threshold (see also De Courson & Nettle, 2021).

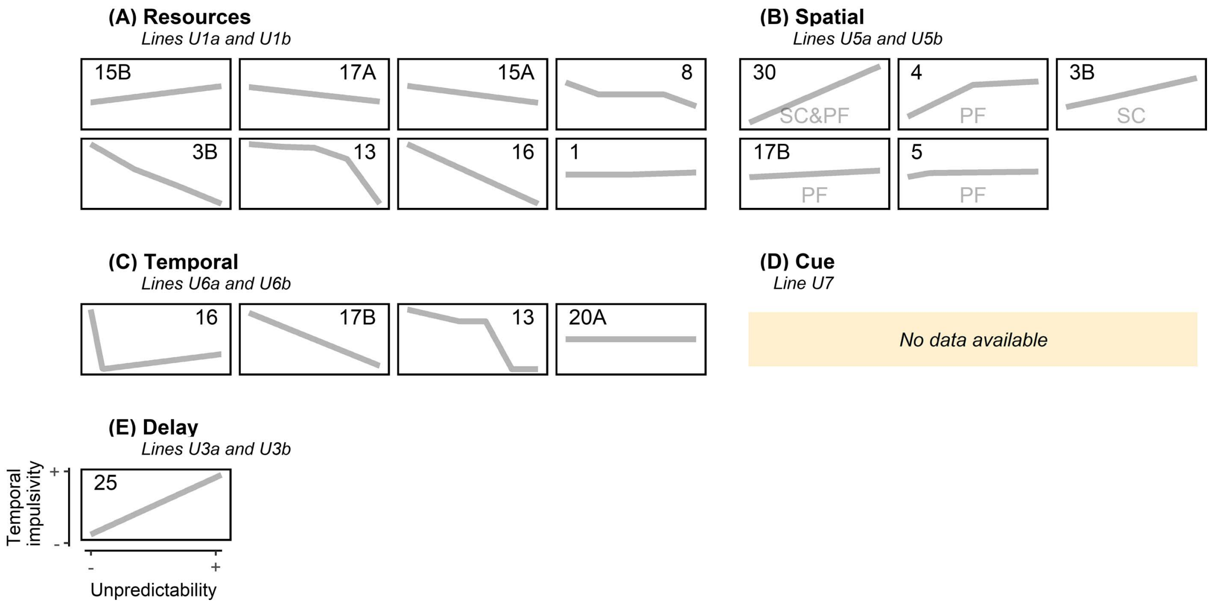
When resources are extremely scarce, temporal impulsivity is maladaptive again, as seen in all six results in Figure 7 that include likely starvation. In these environments resources are either extremely infrequent (#1B), or have a very low mean quality (#1A, #4B, #4C, #5, and #27). Consider an agent that needs to collect a sufficient number of resources within a given time window (e.g., paying the rent by a specific date). If resources are extremely scarce, repeatedly going for a smaller and sooner reward may not be sufficient to stay above a critical threshold. Rather, only a high reward can prevent a costly catastrophe. If so, waiting may or may not save the agent, but temporal impulsivity will certainly result in a catastrophe.

How Unpredictability Shapes Temporal Impulsivity

Resource and Temporal Unpredictability

We found 12 results in eight models that explore how resource and temporal unpredictability shapes temporal impulsivity (Figure 8, Panel A: #1, #3B, #8, #13, #15A, #15B, #16, and #17A and Panel C: #13, #16, #17B, and #20A). Nine results show that temporal impulsivity is maladaptive unless: resources are predictable (i.e., low resource unpredictability) or the environment is stable over time (i.e., low temporal unpredictability; #3B, #8, #13, 15A, #16, #17A,

Figure 8
How Unpredictability Shapes Temporal Impulsivity



Note. Each panel represents one formal modeling result. Table 1 indicates which model corresponds to each number or number–letter pair. Panels are ordered by slope, starting with monotonic positive slopes, followed by slopes that can be positive or negative, followed by monotonic negative slopes, and finishing with (almost) flat slopes. Models that study patch-foraging decisions are marked with "PF," whereas models that study self-control decisions are marked with "SC." The *x*-axis shows unpredictability, ranging from the lowest level of unpredictability in that model ("−") to the highest level ("+"). The *y*-axis shows what level of temporal impulsivity is adaptive, ranging from low ("−") to high ("+"). See the online article for the color version of this figure.

and #17B show this result; #1 and #20A show no effect; and #15B shows the opposite result).

If resources are predictable, they either all have a comparable quality or an agent can reliably estimate the quality of all resources. If they are comparable, the first resource an agent encounters will be similar to the best possible resource. It can wait, but waiting does not result in finding better resources. Temporal impulsivity reduces wait times, without reducing outcomes. In a temporally stable environment, individual resources might still vary, but the distribution of resources remains the same over time. This allows an agent to estimate which resources may become available in the future. It should wait only if it expects that the benefit of waiting is higher than the cost of waiting. If an agent needs to wait a long time for better resources, sooner and smaller resources provide a higher rate of gain.

In a resource-unpredictable or temporally unpredictable environment, temporal impulsivity is maladaptive. If there is resource unpredictability, an agent does not know which resources it will encounter after a delay (#3B, #8, #13, #15A, #15B, #16, and #17A, although #1 finds no effect). The same is true when the environment is temporally unpredictable (#13, #16, and #17B, although #20A finds no effect). Some resources will be good; others poor. However, an agent is very unlikely to encounter the best possible resource first. It is much more likely to first encounter a below-average resource. An agent's options are likely to improve if it waits, hence temporal impulsivity is maladaptive.

Moreover, if there is temporal unpredictability, there are many encounters in between environmental changes (#17B). If the environmental state changes for the worse, resources can be scarce for long periods. For instance, during an economic depression, wages drop for a prolonged period. During such "lean periods," an agent might not be able to collect enough resources to avoid critical thresholds. Although an agent cannot control nor avoid environmental changes, it can safeguard against its effects by building up a reserve. The best way of building up a reserve is to maximize resource intake by going for the option that has the highest rate of gain, even if that implies waiting.

Spatial Unpredictability

We found five results in five models that explore how spatial unpredictability shapes temporal impulsivity (Figure 8, Panel B: #3B, #4, #5, #17B, and #30). In some models, agents are born into patches they cannot leave, and agents do not know the quality of their patch. In this case, an agent needs to decide which minimum resource quality it is willing to accept (this is also called a *self-control decision*; results marked "SC" in Figure 8B: #3B and #30). Setting a higher minimum threshold (i.e., being choosy) implies waiting longer for a high-quality resource. If an agent is unselective, it chooses resources that are immediately available, even if these are of lower quality. Deciding on a minimum level comes with two risks. First, if its minimum is too low, an agent risks missing opportunities when the patch is better than expected. Second, if its minimum is too high, it might have to spend a long time waiting when the patch is worse than expected. In extreme cases, there might not be any desirable resources. These costs are asymmetric: It is often much worse to end up empty-handed than to leave money on the table. An agent should err on the side of caution by placing more weight on the risk of missing out. Keeping its minimum to a fixed level, more spatial unpredictability implies that there are more patches in which an agent ends up empty-handed. To avoid that undesirable situation, an agent should use a lower minimum when patches are more unpredictable. Thus, when patches differ substantially in their quality, it tends to be adaptive to be more temporally impulsive.

Spatial unpredictability has less influence on temporal impulsivity if an agent can move between patches (also called a *patch-foraging* decision; results marked "PF" in Figure 8, Panel B; #4, #5, #17B, and #30). This ability changes the decision in a subtle but important way. Rather than having to make a self-control decision between a smaller sooner reward versus a later and larger one, it now has to decide whether to stay in its current patch or leave in search of greener pastures. According to the marginal value theorem (Charnov, 1976), an agent should remain in its current patch as long as it expects resources there to be better than the average resource quality in all the other patches. An agent is said to be temporally impulsivity if it stays in a patch for too long to forage immediately available resources, while there are greener patches elsewhere. However, the travel time between patches tends to be substantially longer than the wait time between resources within a patch. For instance, a paycheck may come every 2 weeks, but it may well take months to find a new job. If so, any time "wasted" by staying in the current patch is small compared to the total travel time. As a result, the costs of being impulsive and staying too long tend to be relatively low. Due to these lower costs, it is less costly for an agent to be impulsive in a patch-foraging decision than when it is impulsive in a self-control decision. Consequently, spatial unpredictability has less influence on temporal impulsivity in patch-foraging situations (three out of four results marked "PF" in Figure 8B show little or no effect).

Delay Unpredictability

When delays are unpredictable, an agent does not know how long it has to wait for a future outcome (e.g., a job seeker does not know how long the wait is until the next vacancy becomes available). Such unpredictable delays do not affect an agent if it faces a single decision to postpone; in that case, the agent simply accepts the unknown delay to obtain the larger later reward. In contrast, if the agent needs to repeatedly decide whether to wait and delays are unpredictable—as in receiving job offers distributed across time—then it should be temporally impulsive. To be clear, we make this prediction with caution because our analysis included only one model of delay unpredictability (McGuire & Kable, 2013, [#25]).

Some delays are at least somewhat predictable—for instance, when the delay duration is sampled from a normal (or Gaussian) distribution. Consider an individual who interviews for a job opening. A job seeker might not know exactly how long the interview will take but might believe that interview lengths are sampled from a normal distribution with a certain mean (e.g., 90 or 120 min). Every passing moment brings the end of the interview closer; the expected time remaining predictably decreases every minute. All else being equal, if an agent was willing to wait at the onset of the delay, it becomes increasingly more willing to wait as time passes and the remaining delay becomes shorter (i.e., less temporally impulsive).

Other delays are unpredictable—for instance, when the delay duration is sampled from a heavy-tailed distribution (McGuire & Kable, 2013, [#25]). If so, the estimated remaining delay increases when the agent waits longer. Consider an individual that applied to a position. This individual might initially expect a quick reply because they expect few other applicants. However, as time goes by, they might infer that there were multiple contenders, resulting in a longer selection procedure. In this case, the expected time remaining increases over time. All else being equal, even if an agent was willing to wait when the encounter began (e.g., after submitting an application), it becomes less willing to wait as time passes and the remaining delay becomes longer (i.e., more temporally impulsive).

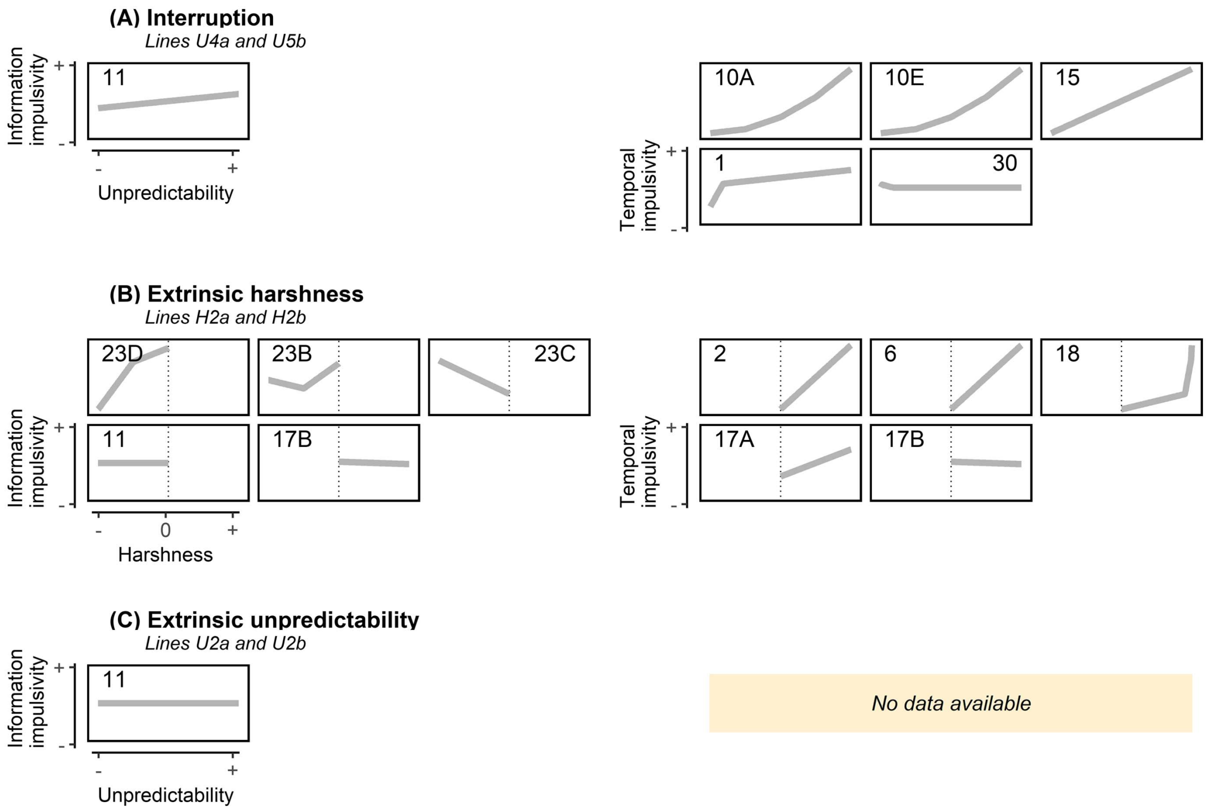
Sometimes an agent does not know from what distribution a delay comes. For instance, an agent might initially believe that the duration of delays is normally distributed. However, after a surprisingly long wait, it might conclude that delays come from a heavy-tailed distribution. In such cases, waiting for a long time increases the likelihood that an agent needs to subsequently wait for a longer time, favoring being more temporally impulsive (McGuire & Kable, 2013, [#25]; see also Griffiths & Tenenbaum, 2006).

How Interruptions Shape Information and Temporal Impulsivity

We found six results in five models that explore how interruptions shape information and temporal impulsivity (Figure 9, Panel A: #1, #10A, #10E, #11, #15, and #30). Five results show that both temporal and information impulsivity are adaptive when interruptions are common (i.e., when resource might become unavailable; #1, #10A, #10E, #11, and #15; only #30 shows no effect), interruptions can occur at any time. Such circumstances make waiting for a future outcome risky (i.e., increases outcome variance); the longer one waits, the more likely a resource encounter is interrupted. The possibility of an interruption typically reduces the subjective value of an outcome. This reduction is inversely proportional to the likelihood of interruptions: Higher interruption rates typically favor steeper reductions. In extreme cases, where interruptions are very likely to occur (e.g., there are many competitors who might take a job before the agent gets it), there is little point to waiting or sampling. Here, an agent should get what it can before the resource becomes interrupted.

The idea that interruptions increase impulsivity is central to models developed in different disciplines: the discounted utility model in economics (Frederick et al., 2002), the hyperbolic discounting model used in judgment and decision-making (Mazur, 2000, 2001), and foraging models in biology (Stephens, 2002). Formal models provide more detail about why and when interruptions promote higher rates of discounting. For instance, although interruptions may explain impulsivity when delays occur over longer timescales, such as weeks or months, they are less likely to explain discounting over shorter timescales, such as seconds or minutes. When delays are long, even a small chance of interruption in the short term reduced the probability that an agent will be able to collect a later resource (Mell et al., 2021). In contrast, there is less compounding over short timescales, such as seconds to minutes. This means that interruption rates have to be very high to explain the high levels of discounting animals show in experiments that examine delays lasting seconds to minutes. For instance, based on empirical results, Stephens and colleagues (Stephens & Anderson, 2001; Stephens et al., 2004; Stevens &

Figure 9
How Interruptions and Extrinsic Events Shape Information and Temporal Impulsivity



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Stephens, 2010) estimate an animal's valuation of a reward drops by 7%–10% in the first second of waiting. They note that for interruptions to explain such a drop, an animal would have to expect 4.2 interruptions per minute. Although such a high frequency might apply to some situations (e.g., foraging birds in a busy patch), it is less likely to apply to the challenges central to impulsivity research with humans (e.g., searching for jobs).

How Extrinsic Harshness Shapes Information and Temporal Impulsivity

We found 10 results in six models that study how extrinsic harshness shapes temporal and information impulsivity (Figure 9, Panel B: #2, #6, #11, #17A, #17B, #18, #23B, #23C, and #23D). Four out of five results that explore temporal impulsivity show that extrinsic harshness increases temporal impulsivity (#2, #6, #17A, and #18 show this pattern; #17B shows no effect). On the other hand, it has an inconsistent effect on information impulsivity, with one result in Figure 9B showing a positive relation (#23D), one a negative relation (#23C), one both (#23B), and two show no relation (#11 and #17B).

Besides interruptions, extrinsic harshness is another reason why delays lower subjective value. An agent's state may deteriorate over time, through disease or death, to where it is no longer able to collect a resource. For instance, the agent's phenotype may have deteriorated while waiting or sampling, potentially increasing the cost of collection. Such deterioration is more likely if an agent's phenotypic state is close to a critical threshold. Whereas interruptions stop only a single encounter, falling below a critical (health) threshold might stop all future encounters. Although in principle extrinsic events might be beneficial (e.g., unprompted financial and social support), only one model has explored extrinsic events with beneficial effects (#11); all other models only include negative extrinsic events.

Some models manipulate extrinsic harshness by including small events that repeatedly damage an agent's phenotype (results in Figure 9 that include low levels of extrinsic harshness: #11, #23B, #23C, and #23D). Whether small negative extrinsic events affect information impulsivity depends on an agent's phenotypic reserve and the mean resource quality.

When an agent's phenotypic state is poor (e.g., it has little money in the bank or is close to starvation), critical thresholds loom large. By definition, an agent cannot avoid the outcome of extrinsic events. However, it can reduce the risk of falling below a critical threshold by building up reserves (e.g., storing money for a rainy day). Depending on the resources in its environment, information and temporal impulsivity can either help or hinder building up reserves. If resources are plentiful or only moderately scarce, an agent should thoroughly search its environment for resources as extrinsic events become more negative (#23C). As a consequence, information impulsivity is maladaptive in these environments. If resources are very scarce, it can no longer afford to sample information and should prioritize immediate survival. Here, information impulsivity is adaptive because it reduces the cost of sampling (#11 and #23B).

When an agent has sufficient reserves to ensure immediate survival, small extrinsic events have little influence on whether it should sample. Sampling depends on the sampling cost relative to the benefit of information. Extrinsic events do not influence resource quality. If an agent can afford to sample, and sampling is beneficial, it should do so, regardless of extrinsic events. In this case, extrinsic events are merely "noise" to be ignored (#11 and #23B).

Finally, when an agent has a large buffer of reserves, critical thresholds are unlikely to loom large in the near future. In this case, an agent can safely invest resources into exploring its environment for high-quality resources (sampling as luxury, #23D). However, this luxury is not granted if extrinsic events are very common, as this implies the possibility of future hardship (a streak of negative events), even if an agent is currently well-resourced. If extrinsic events are very common, information impulsivity helps an agent to maintain its current reserves to insure against future misfortune.

Other models manipulate extrinsic harshness by including events that result in immediate death, regardless of an agent's current phenotypic state (Figure 9, Panel B, results that include high levels of extrinsic harshness: #2, #6, #17A, #17B, and #18). When extreme extrinsic events are frequent, critical thresholds are always close. This increases the adaptive value of temporal impulsivity; an agent should get what it can, while it still can. It is not worth waiting for later outcomes, even if these are better. As Stephens and Anderson (2001) put it, "food that becomes available after you've starved to death is not useful" (p. 330). The subjective value of future outcomes is lowered proportional to the probability that an agent will not be able to consume the resource. As a result, increasing the likelihood of very negative extrinsic events has the same qualitative effect on temporal impulsivity as increasing the likelihood of interruptions, albeit for a different reason.

Discussion

Are impulsive behaviors an adaptive or maladaptive response to living in harsh or unpredictable environments? The current literature on this topic has provided insight, but it is limited by conceptual confusion and practical limitations. Formal models can help to address these limitations. To date, however, findings of these formal models have not been integrated, limiting their impact on the broader impulsivity literature. Here, we surveyed formal models of impulsivity across disciplines. Based on this survey, we developed a conceptual framework that captures key features of formal models of impulsivity across disciplines, allowing us to express different models in a common language. Using this framework, we systematically reviewed and integrated 30 models from psychology, biology, economics, and the management sciences. We found that impulsive behaviors can be adaptive, even when they have long-term costs, if these costs are counterbalanced by benefits. Our model synthesis and findings are useful for theoreticians to see how different theories about impulsivity relate to each other (e.g., similarities and differences in their assumptions and predictions), for modelers to see how specific models relate to each other, and for empirical researchers to see which predictions depend on specific scenarios and which ones are robust across many scenarios, thus providing guidance in designing empirical studies to test between models.

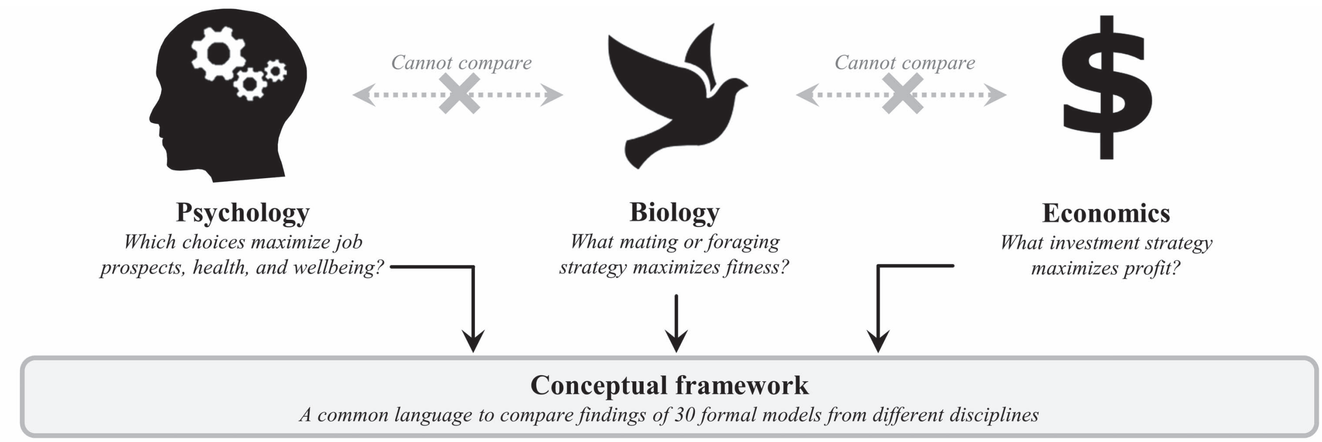
Before discussing implications and limitations, we first summarize our findings in six broad conclusions. The first four are supported by multiple models that suggest similar patterns. The last two are supported by fewer models. Figure 10 provides a graphical abstract of the first four results.

First, both information and temporal impulsivity are adaptive when an individual is close to a critical threshold, such as bankruptcy. Having a low phenotypic state is dangerous, as any negative resource (e.g., buying a car that turns out to have hidden defects) or negative extrinsic event (e.g., missing work due to illness) could result in falling below a critical threshold (e.g., having insufficient money to pay rent and getting evicted). To safeguard against such imminent threat, an individual should store reserves that act as a buffer. Here, both information and temporal impulsivity are adaptive, as they increase short-term available resources and avoid sampling costs, allowing the individual to quickly accrue reserves.

Second, resource scarcity can increase or decrease the adaptive value of information and temporal impulsivity, depending on the type and degree of scarcity. When resources are scarce because they are infrequent (e.g., there are few job vacancies), an individual occasionally encounters a resource, with long delays in between. Rather than waiting for future resources, the individual should focus on collecting immediately available resources. Moreover, knowledge gained from sampling new experiences is worth less, as there are fewer subsequent occasions where this knowledge can be used, increasing the adaptiveness of information impulsivity. Resource scarcity, due to a low mean resource quality (e.g., jobs pay poorly), can increase the adaptive value of impulsivity, if there are fewer good resources available. It has less effect if both future and immediately available have a lower quality (e.g., all jobs pay poorly). Information impulsivity can be adaptive or maladaptive, depending on how information is sampled. Sampling cues helps avoid costly errors (e.g., asking advice before accepting a job), making information impulsivity maladaptive. In contrast, sampling novel experiences might result in negative outcomes (e.g., trying out jobs can result in disappointing experiences), making information impulsivity adaptive.

Third, when the quality of resources is unpredictable, information and temporal impulsivity are both maladaptive. In predictable environments where resources have similar qualities (e.g., wages do not differ between factories), most actions result in similar outcomes (e.g., any job is good). Sampling does not result in more accurate beliefs, and waiting does not result in better outcomes. Accordingly, information and temporal impulsivity are adaptive, as they help avoid sampling costs and minimize possible

Figure 10
A Graphical Abstract of the Present Study's Conclusions



In which environments is impulsive behavior adaptive?

	Harsh environments			Unpredictable environments		Both
	Immediate danger	Resource scarcity		Resources are unpredictable	Resource interruptions	Other
		Poor quality	Infrequent			
Information impulsivity	▲	▲ or ▽	▲	▽	▲	▲▽
Acting without knowing consequences	*Cannot afford to sample when reserves are low*	*Risky to sample experiences. However, can avoid risks by sampling cues*	*Should not waste few resources to explore; instead, exploit what is available*	*Need information to predict outcomes*	*Acquire a resource before it is gone; do not waste time or energy on resources that can disappear.*	*Depends on details*
Temporal impulsivity	▲	▲ or **no effect**	▲	▽	▲	▲▽
Prefering sooner over later outcomes	*Should go for immediate resources when reserves are low*	*Should not wait if there are no better future alternatives; no effect if all outcomes are poor*	*Waiting for better options takes too long*	*First encountered resource is likely below average. Wait for better options*	*Same as above*	*Same as above*

Note. The biology icon was obtained from https://dryicons.com/icon/bird-icon-13097.

interruptions, respectively. When resources are unpredictable, some resources will be good and others not. Sampling information helps an individual to understand which action to take and what the future might hold, making information impulsivity maladaptive. Moreover, when resources are unpredictable, the first resource found is unlikely to be above average. Rather than being temporally impulsive, an individual should wait to find better resources later.

Fourth, when interruptions are frequent, temporal and information impulsivity are both adaptive. An interrupted resource has no value; a job vacancy filled before an individual can apply is useless to that individual. Moreover, information about the quality of a resource cannot be used to inform immediate actions. This makes sampling cues a risky investment if interruptions are likely. Rather than wait or sample, an individual should get what they can before the resource is gone. However, interruptions must occur often before impulsivity becomes adaptive. Although such a high frequency likely applies to some situations (e.g., foraging birds), it is less likely to apply to the challenges central to impulsivity research with humans (e.g., spending or saving money, settling or searching for jobs or mates).

Fifth, when environments change unpredictably over time, temporal impulsivity is maladaptive, and information impulsivity can be adaptive or maladaptive, depending on how often changes occur. Temporal unpredictability has the same effect on temporal impulsivity as resource unpredictability: If the environment changes stochastically, an individual will likely find better quality resources later on. In contrast, temporal unpredictability has a U-shaped effect on the adaptive value of information impulsivity. In temporally stable environments, information is never outdated. However, it also accumulates with diminishing returns: As an individual comes to know more about world, their beliefs are less likely to change due to additional information. An individual should sample information only early on in life. After that, an individual can reduce sampling costs by being informationally impulsive. In moderately temporal unpredictability, the environment changes multiple times during a lifetime (e.g., semi-regular economic recessions). Here, an individual has to continuously sample information to keep their beliefs accurate, making information impulsivity maladaptive. Finally, in temporally very unpredictable environments, conditions may change from day to day (e.g., the availability of jobs depends on volatile weather conditions). The future cannot be predicted at all, implying no benefit (only costs) to sampling, making information impulsivity adaptive.

Sixth, in spatially unpredictable environments, information impulsivity is maladaptive, whereas temporal impulsivity tends to be adaptive. Spatial unpredictability has the same effect on information impulsivity as resource unpredictability does: If local patches differ in quality, an individual should sample information to develop a better estimate of the state of the current local patch, making information impulsivity maladaptive. Moreover, an individual needs to decide what the lowest resource quality is that is acceptable and search until they find a resource that meets this criterion. Setting a low minimum typically means finding an acceptable resource sooner, implying temporal impulsivity. Being choosy by setting a high minimum typically means waiting longer, implying low temporal impulsivity. By not being choosy enough, an individual risks missing out on better resources when the local patch is better than expected. However, by being too choosy, an individual risks ending up empty-handed when the local patch is worse than expected. As ending up empty-handed often is much more costly than leaving money on the table, it tends to be adaptive to err on the side of being temporally impulsive when there is spatial unpredictability.

Recommendations for Empirical Research

Our review and six broad conclusions provide testable hypotheses for future empirical research. Currently, it is difficult to estimate the degree to which existing empirical results align with these conclusions. On the one hand, there is empirical support for the first four conclusions. For instance, previous studies found that people are more temporally and informationally impulsive when (a) they face immediate threats to their resources, such as bankruptcy (Hilbert et al., 2022; Mell et al., 2021; Pepper & Nettle, 2017; Sheehy-Skeffington, 2020); (b) they live in certain types of harsh environments (Bulley & Pepper, 2017; Kruger et al., 2008; Otto et al., 2012; Pepper et al., 2017; Ruggeri et al., 2022), though perhaps not in other types of harsh environments (Copping et al., 2013, 2014; Kometani & Ohtsubo, 2022; Otto et al., 2012; Pepper et al., 2017; Ruggeri et al., 2022); (c) grow up in unpredictable environments (Brumbach et al., 2009; Hartman et al., 2018; Kidd et al., 2013; Lee & Carlson, 2015); and (d) when resource interruptions are common or likely to occur (Frederick et al., 2002; Mazur, 2000; Story et al., 2014). However, to our knowledge, there are no systematic meta-analyses of the relevant empirical data. Without a principled survey of the empirical literature, it is unclear whether these studies are a representative sample or whether there are (unpublished) studies that suggest other conclusions. Moreover, our conclusions imply predictions about some environmental dimensions that, to our knowledge, have yet to be studied empirically in relation to impulsivity. For example, few empirical studies have actually measured spatial or temporal unpredictability in mortality or resources—even though such data are available (Frankenhuis et al., 2019)—and none have examined how such dimensions shape different types of impulsivity. Our conclusions help empirical researchers by showing to which environmental conditions particular empirical predictions apply (the first four conclusions), offer novel hypotheses about thus far unexamined environmental dimensions (the last two conclusions), and provide future meta-analyses with an inventory of which environmental dimensions are particularly important to include. Our work thus sets the stage for an empirical synthesis that would fill a major gap in the literature. In addition, we provide four specific recommendations for future empirical research.

First, researchers should employ precise definitions of harshness, unpredictability, and impulsivity. Whether impulsive behaviors are adaptive or maladaptive depends on the type of impulsivity and the type and degree of harshness and unpredictability. For instance, our analysis shows that harshness and unpredictability can increase the adaptive value of information impulsivity, while at the same time decrease the value of temporal impulsivity or vice versa. To be able to discern such opposing effects, we need clear definitions of harshness and unpredictability. Teasing apart the separate effects of different environmental dimensions is also challenging because they tend to be empirically correlated (e.g., resource scarcity and unpredictability). Carving these correlated data at those joints that shape different types of impulsivity requires explicit—ideally, formalized—definitions of harshness, unpredictability, and impulsivity. Such clarity also helps in evaluating in which studies empirical predictions follow deductively from assumptions (rather than having been intuitively derived) and to match descriptions of environmental dimensions across studies (e.g., when different studies have used different terms to refer to the same construct), enabling meta-analysists to see how concepts and predictions in different studies relate to each other.

Second, researchers should use explicit operationalizations of harshness, unpredictability, and impulsivity. Even when using identical (formalized) conceptual definitions, researchers often use different operationalizations. For example, as we already noted in the How Resource Scarcity Shapes Information Impulsivity section, information impulsivity can entail not sampling cues or not sampling experiences, and these are adaptive in different environments. Similarly, temporal unpredictability can be operationalized as the temporal autocorrelation in resource availability (e.g., whether the number of vacancies today predict the number of vacancies tomorrow), as the frequency of changes in resource availability (e.g., the frequency of economic recessions), and there are other options (Walasek et al., 2022). To facilitate comparisons across studies, we recommend empirical researchers to be as explicit as possible about their operationalizations.

Third, when possible, empirical research should measure each environmental dimension on at least three levels. This is because environmental dimensions can have nonlinear effects on impulsivity, and such nonlinear patterns cannot be detected if only two measurement levels are used. For instance, our findings suggest that information impulsivity is adaptive when environments are moderately temporally unpredictable, but maladaptive when environmental unpredictability is high or low. If the environment is measured at only two values—or multiple values in close proximity—effects on impulsivity will always appear linear, even when in reality they are not. Measuring environmental dimensions on at least three different points can also have other beneficial effects by prompting researchers to include diverse participants in research, for instance, people from at least three different socioeconomic strata.

Fourth, researchers should consider phenotypic states and critical thresholds. Behavior that is adaptive for individuals that have strong phenotypic reserves (e.g., sufficient savings) might be maladaptive for those missing such reserves (e.g., having to struggle to make ends meet) and vice versa. For instance, moderately extrinsic events can be ignored when an individual has sufficient reserves. In contrast, when close to a critical threshold (e.g., being evicted), such events might promote temporal impulsivity. To understand when impulsivity is adaptive, we need to measure an individual's current phenotypic state (e.g., financial or health) and the thresholds relevant to their behavior. Moreover, people are sometimes slow to adapt to changing phenotypic states. For instance, after financial hardship, and individuals might remain focused on preventing future hardships, even if resources are currently plentiful. In such cases, an individual might only be willing to wait for later outcomes and try out novel experiences after having been affluent for an extended period of time. To address this issue, it is better to use longitudinal designs rather than cross-sectional ones.

Implications for Interventions and Policy

Impulsivity can be adaptive for some outcomes, yet have other undesirable consequences. We explored in what environments impulsive behaviors are adaptive; that is, when being impulsive maximizes long-term outcomes. However, individuals often face trade-offs between competing outcomes: What is adaptive behavior in the light of one outcome can be maladaptive for another. Working a job that has a poor fit might result in a stable income, yet comes at a cost of long-term satisfaction and well-being. Further, behaviors that are adaptive need not be socially desirable. For instance, in violent environments, people might learn to use coercion to obtain social status or to respond quickly and aggressively to perceived disrespect to deter others in the future. Even if such aggressive behaviors might be adaptive for an individual living in a harsh context, from a societal perspective, a milder response is more desirable. Despite this crucial distinction between "adaptive" and "socially desirable" behavior, our findings may have three implications for policy and interventions.

First, insights from models help predict and prevent adverse side effects. Interventions often focus on reducing impulsivity by changing individuals' traits and states. For example, they aim to promote deliberation, planning, and future orientation through forming implementation intentions (Gollwitzer, 1999), providing attention training (Murray et al., 2016), or go/no-go training (Veling et al., 2014). However, if the environment incentives high levels of impulsivity, interventions that reduce impulsivity without changing environmental conditions can have adverse side effects. Suppose that reacting quickly and aggressively to perceived insults and disrespect helps secure long-term safety. If so, an intervention to decrease (information) impulsivity might reduce the overall levels of aggression. However, without changing the environment, this reduction may come at a cost of long-term safety. After all, there may have been a reason why aggression was "profitable," at least for some individuals. Moreover, this cost is specific to people who adhere to the interventions. In some cases, these side effects reduce adherence to intervention programs, limiting their positive effects. In others, they may do active harm to participants (e.g., through the loss of social status and long-term safety). To be successful, interventions need to change environmental conditions, alongside individual-level traits and states (for a similar conclusion, see Chater & Loewenstein, 2022).

Second, insights from formal models help predict the success of an intervention that targets environmental dimensions. As an example, our findings suggest that temporal impulsivity is adaptive not only when critical thresholds are close but also when resources are infrequent or interruptions are common. This insight can inform interventions designed to increase future orientation for people living in harsh environments. For instance, it suggests that a single lump-sum payment to decrease immediate hardship (by avoiding a critical threshold) is unlikely to reduce temporal impulsivity, if it does not also increase the frequency of resources and the predictability of future payments (by reducing interruptions).

Third, formal models can suggest alternative dimensions to target. For example, rather than providing a lump-sum payment, a more effective intervention might be to consistently provide smaller payments over longer periods (assuming budgetary constraints preclude the possibility of consistently providing larger payments), decreasing both immediate hardship, resource harshness, and interruption unpredictability.

Implications for Modelers and Theoreticians

There has recently been a surge of calls for a common (formal) language to make psychology a more cumulative science (Eronen & Romeijn, 2020; Gigerenzer, 2010, 2017; Leising et al., 2021; McPhetres et al., 2021; Meehl, 1990; Smaldino, 2019). Psychology is home to many competing—in some cases mutually exclusive—theories. Mischel (2008) quipped that social scientists treat other peoples' theories like toothbrushes; no self-respecting person wants to use anyone else's. Due to this fragmented state, the social science landscape consists of many islands of disparate ideas, procedures, and knowledge. Formal theories can build bridges between islands by clarifying how ideas are related and how they are different (Frankenhuis & Tiokhin, 2018; Muthukrishna & Henrich, 2019; Oberauer & Lewandowsky, 2019; Smaldino, 2020; for an example, see Schlüter et al., 2017). We support this call and hope the current research offers a step toward better theoretical integration of impulsivity research, thus contributing to a cumulative science of decision-making more generally.

We see two major challenges to the growing practice of formal modeling in the social sciences. The first is that the generalizability of any model's findings depends on how well the assumptions of that model match the reality of a given setting (Smaldino, 2017; Van Der Leeuw, 2004; Wimsatt, 1987). This match is often difficult to assess, making it difficult to understand if, and to what extent, modeling results translate to qualitative empirical predictions. In the next section, we discuss how future models can improve realism. Second, as we discuss in the introduction, there has been little integration of formal models, making it difficult to understand how different models are related and how they differ. This makes it difficult to connect the dots, making it difficult to understand what pieces of a puzzle are known, how they fit together, and which pieces are still missing. It is, for instance, not immediately clear how a formal model studying foraging behavior can inform theory on impulsive behaviors in organizational settings.

Our conceptual framework provides a common language, which can help with both challenges. By expressing models in similar terms, we were able to combine multiple models that make different assumptions. When different models produce similar patterns, we can be more confident that a conclusion does not depend on the specific assumptions of any given model, but rather that we have identified as robust theorem. That is, although each individual model is limited, by amassing the results from a family of models, each of which having different assumptions and limitations, we learn general lessons. To paraphrase Levins (1966), we find truth at the intersection of independent lies. Moreover, expressing models in similar terms helps us understand which pieces are still missing (discussed in the next section). In this review, we have assessed whether temporal and information impulsivity are adaptive across a range of environmental conditions. This approach, however, is general and can also be used for other topics in the social sciences, such as risk-taking, sensation-seeking, peer relations, anxiety, depression, aggression, or life history development.

Limitations and Future Directions

Several limitations constrain the generalizability of our conclusions. These limitations fall in two broad categories: methodological limitations and gaps in the literature on formal models of impulsivity. We discuss each in turn and provide future directions to address these constraints.

Methodological Limitations

We consider four methodological limitations to our work. First, despite our best efforts, there is no guarantee that we surveyed all the eligible models. Our review spanned multiple disciplines and diverse terminologies. This heterogeneity made it difficult to capture all relevant keywords. It is possible that we missed clusters of articles that used terms not included in our search. Moreover, due to the interdisciplinary nature of our analysis, it was not feasible to exhaustively search the gray literature. However, we do not think that our necessarily constrained search biased our results, as we suspect that the decision to publish a formal model depends on the quality of the research question, methods, and interpretation, more so than on the outcome of a model. We also did not explicitly survey the non-English literature—although non-English articles would have appeared in our survey if they used terms matching our search string. As with all systematic reviews, future studies can include search terms left out here. Finally, part of our literature search was done using Google Scholar. This search is not reproducible as Google Scholar lacks accession dates and continuously expands its database by including both current and past publications (Gusenbauer, 2019).

Second, we constructed our framework based on our reading and interpretation of the literature. We did not use any structured or systematic approaches. Other scholars might carve the environment in different dimensions and highlight other decisions, including more or fewer details. For instance, we split up harshness into resource scarcity and extrinsic events. Alternatively, we could have split up resource scarcity further into resource infrequency and poor resource quality. Similarly, cues might provide information not on resources, but on the (future) state of a patch, the likelihood of interruptions, or the duration of delays. We did not include such cues in our framework because no models we reviewed included them. However, future models that do explore such cues can be incorporated into our framework by using the approach we have developed.

Third, by standardizing environmental dimensions and impulsivity measures, we lost some sense of their range across studies. As discussed in the Defining Harshness, Unpredictability, and Impulsivity section, environments and impulsivity can be operationalized in many ways, making it difficult to compare dimensions. Standardizing within models allowed us to express results on a scale relative to that model (i.e., high vs. low scarcity). However, what is "harsh" in one model might be "moderately harsh" in another. For instance, in some models, a resource-scarce environment meant that food was in short supply (but never poisonous; Campbell & Persaud, 2008). In other models, it implied that wrong mating choices reduce the number of offspring (Henshaw, 2018). We provided some nuance in Figures 5, 6C, 7, and 9B by adding reference lines (e.g., Figure 5 distinguishes between models where resources can also have negative qualities). However, is it difficult to express exactly how models related to each other on the severity of harshness and unpredictability. We see a possible solution: A common modeling conceptual framework can harmonize models. Specifically, formal modelers can work on a universal language in which environmental dimensions can be standardized.

Fourth, we did not provide a single estimate for how each environmental dimension shapes different types of impulsivity. Meta-analyses often combine multiple observed effect sizes into a single summary statistic that represents a best estimate of the true effect size. We could have similarly combined patterns that study how a particular environmental dimension shapes one type of impulsive behavior (e.g., a single estimate of how resource harshness shapes information impulsivity averaged over the 15 panels in Figure 5). We chose not to do so, as the models in our analysis differed substantially, both in their assumptions and the decisions they studied. For instance, whereas some models studied information impulsivity when sampling cues, others studied information impulsivity when sampling experiences. Our results showed that sampling cues or experiences was an important moderator: In resource-harsh environments, not sampling cues is maladaptive, whereas not sampling experience was adaptive. Similar to how a main effect is difficult to interpret in the presence of moderators, a single average pattern would be difficult to interpret when models differ widely. Instead, we both discussed what pattern the majority of models showed, and why other models showed different results. However, future reviews that use a similar methodology to review and integrate more homogeneous models can consider including summarizing statistics to express a common result and assess whether that result is robust to small differences across models.

Gaps in the Formal Modeling Literature

Our review and synthesis revealed several gaps in the literature on models of impulsivity: environmental dimensions, decision mechanisms, and other dynamics that influence real-life impulsivity. The reduction in realism resulting from these gaps can hamper the generalizability of our results. Here, we discuss four missing aspects of how individuals make decisions and three missing environmental dimensions to be studied.

Future Models Can Include Mechanisms and Constraints. We have analyzed models of optimal behavior. Such models take an ultimate-level perspective that studies function, rather than taking a proximate-level perspective that studies mechanism. That is, they study *why* behavior occurs, rather than *how* cognitive mechanisms produce impulsive behaviors, or *how* environmental patterns elicit such behaviors. Such models are not intended to mimic psychological processes, but rather to "identify the optimal strategy from the perspective of an observer, without discussing how the decision maker might achieve it" (Kacelnik, 2012, p. 25). This approach assumes that decision-making mechanisms instantiate optimal behavior absent (phylo)genetic, developmental, or other constraints. In behavioral ecology, this assumption is known as the *behavioral gambit* (Fawcett et al., 2013). However, in the real world, there are many social, cultural, physiological, genetic, computational, or otherwise practical constraints that prevent an individual from acting optimally. Models of information impulsivity typically assume that organisms can behave as if they perform Bayesian updating, even though Bayesian updating is computationally expensive at best, and completely intractable in most realistic environments (Trimmer et al., 2012; van Rooij et al., 2018).

Despite downsides, we consider the behavior gambit a feature for some purposes, not a bug. It is a useful simplification when developing and testing initial models of behavior. By abstracting away details, formal models reveal general patterns. Moreover, their abstract nature made it possible for us to synthesize results across disciplines, increasing the scope of models included in our review. Most models included in our analysis studied nonhuman animal behavior, but due to their abstract nature, they still made few if any species-specific assumptions. Without such assumptions, there are few differences between an abstract forager searching for food and an abstract human searching for jobs, facilitating integration across formal models.

On the one hand, this abstract nature limits the scope and realism of modeling results, and consequentially, our conclusions. Most importantly, the abstraction makes it challenging to understand how results from such models translate to specific real-life circumstances. Future models can increase realism by including known psychological mechanisms and environmental patterns that afford or elicit impulsive behaviors. On the other hand, they can explicitly include such mechanisms. For example, a model of when and why people living in poverty behave temporally impulsively can incorporate mental states such as the perception of resource scarcity, which might increase anxiety and reduce time and energy available to plan for the future. Additionally, they can include environmental patterns and affordances, such as an abundance of information that might tax cognition and deliberation, reducing the ability to make informed decisions. Although we think such models can have value, we caution that explicitly including mechanisms can increase the complexity of models. Whether this complexity is worth it depends on the research question.

Alternatively, future models can increase realism by including constraints that result from mechanistic limitations, without explicitly including mechanisms. Here, we discuss four possible constraints and suggest future directions. First, all models in our review assumed individuals can store and process large amounts of information; they also assume that individuals did not face time constraints when making decisions. Future models can constrain both the memory capacity or time available to make a decision. For instance, they can study individuals that use heuristics that humans are known to use (Todd & Gigerenzer, 2000). Moreover, rather than reasoning which action should be taken, individuals often follow the behavior of peers. Relying on such (social) cues reduces cognitive effort and time, shields an individual from blame when outcomes go wrong, and, in some situations, increases accuracy (i.e., the wisdom of crowds; El Zein et al., 2019). However, in other circumstances, relying on the insights of peers might result in costly errors, for instance, when the collective belief is incorrect or when the interest of the group differs from the interest of the individual. Future models can include such heuristics and environmental affordances (for an example model, see Hall & Kramer, 2008; see also Hertwig & Hoffrage, 2013).

Second, only one model in our review incorporated some notion of development (Frankenhuis & Panchanathan, 2011). All the other models assume fully developed individuals that come "equipped" with all of the skills and abilities that they need. For instance, individuals have the capability to sense, understand, and integrate information and estimate wait times. In organisms in real life, developing such skills takes time and effort. Such investment might be worthwhile in some environments, but too costly in others. For instance, in harsh environments, an individual might have to allocate most resources to survival. If there are sensitive periods of development, an individual experiencing early-life adversity might be better off not investing in developing such skills and abilities. Future models can examine in which environments this investment is worthwhile, and when it is not (e.g., rational inattention; Sims, 2003).

Fenneman and Frankenhuis (2020) discuss how including developmental processes might help to understand two robust empirical patterns. First, impulsivity and risk-taking behaviors are more common in early adolescence (Figner et al., 2009; Steinberg, 2007). One explanation for this peak is that during adolescence, social status becomes more important. Securing high-status positions requires resources, which can be acquired through increased risk-taking (Brumbach et al., 2009; Ellis et al., 2012). Formal models can test the logic of this argument and examine whether this explanation extends to temporal and information impulsivity. Second, (self-report) questionnaire and behavioral measures of impulsivity show little correlation, yet both predict observed impulsivity (Cyders & Coskunpinar, 2011; Reynolds et al., 2006; Stahl et al., 2014). A possible explanation for this pattern is that the two types measure different facets of impulsivity. Questionnaires measure a stable baseline of impulsivity (i.e., trait impulsivity), whereas behavioral tasks measure the capability to deviate from this baseline and tailor impulsivity to match environmental demands. This raises interesting questions such as Is there indeed a stable baseline? If so, why is there a baseline? Why do we not always adjust our impulsivity to match environmental demands? Why do people in similar environments differ in their levels of impulsivity? Is this baseline fixed after a sensitive period or malleable across the life span based on experience?

Third, the models we reviewed typically assumed a homogeneous population with few individual differences. In contrast, in realistic situations, individuals differ in many ways, including in their ability, willingness, costs, and benefits to process information or considering future consequences. Stated differently, people have different personalities, which interact with their environments in different ways to shape the adaptive value of impulsive behaviors. Although these differences can come from following different developmental trajectories, formal models can include such differences without including development. For instance, people differ in their tolerance for uncertainty and need for cognition (Cacioppo et al., 1996) or perhaps more generally in their openness to experiences (Fleischhauer et al., 2010). Future models can incorporate personality differences by considering multiple individuals that have different needs, abilities, or goals.

Finally, all of the models in our analyses investigated impulsivity in a non-frequency-dependent context, meaning that the adaptive value of strategies (or behaviors) did not depend on the strategies (or behaviors) of other individuals in the population. This context applies to certain types of decisions, but not to others. For instance, cultures have different norms on what counts as acceptable or unacceptable behavior. Moreover, cultures differ in the strength of social norms; some cultures have strong social norms and a low tolerance for deviant behavior, whereas others have weaker social norms and higher tolerances (Gelfand et al., 2011). The strength of social norms might influence the adaptive value of impulsive behaviors. For example, having sampled fewer contextual cues, an informationally impulsive individual might inadvertently act in a way that deviates from social norms. If such transgressions elicit punishment, such norm violations can be costly to the individual, promoting lower levels of information impulsivity. Conversely, the prevalence of impulsive behaviors can itself influence dimensions of the environment, such as harshness and unpredictability. For example, if many individuals are temporally impulsive, resources may be more likely to become unavailable in the future. Empirical research shows that in harsh environments (e.g., resources are scarce) and unpredictable environments (e.g., natural disasters or disease are common), cultures may have stronger social norms and lower tolerance of deviant behavior (Gelfand et al., 2011). The coexistence of these behaviors and norms might lead to a coevolutionary dynamic between individual behavior and group norms, in which the cultural environment shapes an individual's behavior, and an individual's behavior subsequently influences the (cultural) environment (for discussion, see Kaufman et al., 2014). Formal models are needed to understand and predict such interactions (Bear & Rand, 2016; Rand et al., 2017). Thus, future theory and research can explore the coevolutionary dynamic between individual-level impulsive behaviors and population-level characteristics, such as social norms.

Missing Environmental Dimensions. We discuss three gaps in the types of environments included in the models we have analyzed. First, only one model studies positive extrinsic events or extrinsic unpredictability (Fenneman & Frankenhuis, 2020). All other models study extrinsic events as a fixed probability of extrinsic mortality (i.e., immediate death due to external causes, such as predation or severe illness) or as fixed reductions in phenotypic state (e.g., increased metabolic rates). This is an unrealistically bleak view; often, extrinsic events can have positive consequences. For example, people often help each other in times of need. Moreover, although instant mortality is plausible in some species and environments, it is unlikely for others. For instance, when foraging, animals risk being eaten by predators. For humans, mortality rates have historically been and remain in contemporary societies, highly variable across time and space. For instance, in a survey of hunter–gatherer and forager-horticulturalists societies, the range of infant and child deaths attributable to violence varied from 1.4% to 63.5% (Gurven & Kaplan, 2007), illustrating diversity in the human childhood experience. In 2017 the global child mortality rates ranged from 0.3% in Iceland to as high as 10% in sub-Saharan Africa (Roser et al., 2019). Finally, extrinsic events are often unpredictable, varying in their consequences. For instance, certain diseases are more detrimental than others. A car breaking down unexpectedly and an earthquake both create property damage, but one is likely to be worse than the other. Future models can include positive extrinsic events, negative but nonlethal extrinsic events, and extrinsic unpredictability.

Second, none of the models studied how negative resources (e.g., losses) affect temporal impulsivity. All of the models studied resource scarcity as either a low mean resource quality or a resource infrequency. However, many decisions people face feature both gains and losses. For instance, someone might consider buying a fuel-efficient car, which has high up-front costs but lower costs later on (Hardisty et al., 2013). Moreover, in very harsh environments, people often have to choose between the lesser of two evils—for instance, between going hungry today or being homeless next month. By neglecting losses, we limit how resource harsh an environment can be. Future models can study losses by including environments in which resources can have both positive and negative qualities.

Third, the models we reviewed studied stylized environments that covered a large range of harshness and unpredictability. Future formal models can narrow this range to match real-world environment conditions. For example, multiple formal models in our review studied temporal unpredictability. Some environments included temporally stable environments, where there was no unpredictability. Other models included environments that change from moment to moment. For most human populations, the temporal unpredictability probably is in between these two extremes. Similarly, other formal models agree that both types of impulsivity are adaptive when interruptions are likely. However, for these interruptions to have a strong effect, they must be very frequent. By some estimates, interruptions have to occur roughly 4.2 times per minute for impulsivity to be adaptive (Stephens & Anderson, 2001; Stephens et al., 2004; Stevens & Stephens, 2010). Although such a high frequency might be realistic for some decisions (e.g., foraging birds in a densely populated patch), it is less likely to apply to the challenges central to impulsivity research with humans (e.g., searching for jobs). Future models might tailor the range of environmental dimensions to specific levels (for a further discussion on using environmental statistics in formal models, see Frankenhuis et al., 2019).

Conclusions

A common claim is that impulsive behaviors are maladaptive as they have long-term costs. The models we reviewed contradict this claim: Impulsive behaviors can be adaptive, even when they have long-term costs, if these costs are counterbalanced by benefits. Although this general insight can be grasped without formal models, understanding how costs and benefits compare, and when impulsivity is adaptive, requires formal modeling. Here, we reviewed and integrated 30 formal models from diverse disciplines based on a novel conceptual framework. This framework affords describing individual models in a common language, in turn enabling model comparison. We conclude with four general insights and associated recommendations:

First, impulsivity is neither universally adaptive nor maladaptive. Rather, the adaptive value of impulsive behaviors depends on the structure of the environment and the type of impulsivity. Therefore, the field would benefit by setting the norm that claims about the adaptive value of impulsive behaviors are accompanied by definitions of key concepts and explicit (ideally, formalized) characterizations of the environment, describing its features (e.g., harshness, unpredictability) in terms of probability distributions, resource distributions, short- and long-term costs and benefits, and other factors relevant to behavioral outcomes.

Second, when individuals have few resources, information and temporal impulsivity might be adaptive for the immediate resources they can yield. Therefore, empirical studies of the adaptive value of impulsivity should measure individual differences in relevant state variables, such as wealth, health, and social status. We advocate for research that contextualizes state and trait variation in impulsive behavior in the context of other variables predicted to influence the costs and benefits of impulsive behavior. Which variables are relevant depends on the question.

Third, when resources are rare or interruptions are common, both temporal and information impulsivity can be adaptive because they help to secure fleeting resources. Temporal impulsivity is more likely to be adaptive when the quality of resources is low. The adaptive value of information impulsivity depends on whether information is gathered by sampling cues versus new experiences. Both types are generally maladaptive when resources are unpredictable. Policy and intervention efforts can benefit from a better understanding of the particular ways in which different types of harshness and unpredictability tend to influence impulsivity (e.g., resource scarcity vs. resource unpredictability).

Finally, by providing a concrete demonstration of the possibility and feasibility of developing a common language and framework for comparing theory across different academic disciplines, we hope our work will contribute to a cumulative science of impulsivity. Indeed, as noted earlier, our approach can be used as a model for researchers who seek to integrate theory across disciplines for other behaviors (e.g., risk-taking, aggression). We ultimately hope our work will contribute to consilience, the integration of all sciences.

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Received December 24, 2021
Revision received September 2, 2022
Accepted September 6, 2022 ■