A Timeline of Cognitive Costs in Decision Making

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Abstract

Recent research from economics, psychology, cognitive science, computer science, and marketing is increasingly interested in the idea that people face cognitive costs when making decisions. Reviewing and synthesizing this research, we develop a framework of cognitive costs that organizes concepts along a temporal dimension and maps out when costs occur in the decision-making process and how they impact decisions. Our unifying framework broadens the scope of research on cognitive costs to a wider timeline of cognitive processing. We identify implications and recommendations emerging from our framework for intervening on behavior to tackle some of the most pressing issues of our day, from improving health and saving decisions to mitigating the consequences of climate change.

Keywords: cognitive effort, decision making, cognitive resources, opportunity cost, algorithmic cost, representations

What are Cognitive Costs?

Research from economics [1–4] and cognitive science [5–8], to neuroscience [9–11] and marketing [12,13] is increasingly focused on the idea that decision-making is costly. A common thread is the assumption that human cognition is guided by a tradeoff between the quality of people's decisions and the cognitive costs associated with making them [14]. Despite this commonality there is heterogeneity across research fields in 1) what is thought to be costly in cognition, 2) how to measure these costs, and 3) how cognitive costs influence behavior [8,15,16].

For instance, in economics, cognitive costs are often conceptualized as sacrificed opportunities and their measurement is relative, denominated in terms of monetary incentives [17] such as willingness to pay [3]. Other disciplines—e.g., cognitive science or neuroscience—operationalize cognitive costs in terms of reaction times or physical signatures such as neurophysiological markers. The conceptualization of these costs focuses on how a particular representation of the decision problem is constructed and held in mind (representational costs [18]) or on the complexity of the computations carried out on these representations (algorithmic costs [6–8]).

This heterogeneity can hinder progress in understanding how cognitive costs shape decision-making. The lack of interdisciplinary crosstalk can create blind spots at the intersection of different disciplines leaving key conceptual questions unaddressed. Attempts to intervene on decisions from a policy perspective could be enhanced by recognizing that different costs require tailored interventions (e.g., reducing computations vs. prompting adequate mental models). Thus, there is a need to integrate the different perspectives on cognitive costs—some overlapping, others distinct—and develop a comprehensive framework of how they influence decision-making.

This review proposes such a framework, highlighting time as a unifying concept that indicates when costs come into play during a decision process. Our review is in two parts. Part one summarizes different conceptualizations of cognitive costs drawn from diverse disciplines with long standing interest in how cognitive costs shape decision-making—including economics, psychology, cognitive science, computer science, and marketing—and then organizes these perspectives along a timeline of cognitive costs (Figure 1, Key Figure). By focusing on when costs occur in the decision process, our framework complements existing accounts that have illuminated the role of limited resources [7,19] (see Box 1 for details on how cognitive costs relate to limited resources), experienced effort [20,21], or the neuro-metabolic processes involved in understanding cognitive costs [11]. Although temporal factors have been considered in influential work on performance monitoring [22], cognitive control [23], or decision-models [24,25], our review offers novel insight into how the timing of cognitive costs impacts decision-making. Part two draws out the policy implications of the temporal framework and shows how it can help to address some of the most pressing issues of our day, from improving individual health and saving decisions to mitigating the consequences of climate change.

The Role of Time in Different Perspectives on Cognitive Costs

The timeline of cognitive costs illustrated in Figure 1 evolved from considering not only the familiar concepts invoked to explain costs during a decision—e.g., algorithmic costs [6,7] and opportunity costs [3,26]—but also those incurred in the lead-up to a decision, such as representational costs [18], and costs following the decision process [27]. Additionally, we draw out temporal aspects not widely considered in research on cognitive costs, such as meta-cognitive costs and entry costs. To pre-empt our subsequent synthesis, we acknowledge the interrelations between and potential temporal overlapping of different costs, but contend that viewing these concepts through a temporal lens helps us better understand when people's decisions are primarily affected by the cognitive costs they incur, thereby facilitating policy recommendations for intervening on their decision-making.

In the Moment of Choice: Cognitive Costs When Making a Decision

Opportunity Costs

Imagine a person deciding whether to engage in a mentally laborious behavior, such as solving a difficult mathematical equation. The concept of opportunity costs assumes that the cost of this behavior is measured relative to the best available alternatives that must be sacrificed to engage in the behavior (e.g., playing on a smartphone). That is, when we engage in a particular behavior, it consumes time (and energy) in that moment, which could be invested elsewhere. This concept of cognitive costs as sacrificed opportunity has traditionally featured in economics research, which regards costs hedonically—as the reduction in personal well-being resulting from a particular behavior. That is, by engaging in the laborious cognitive process, the person is foregoing the alternative of engaging in an activity in which they avoid those negative experiences. Moreover, in psychological research, it has been suggested that people experience a "sense of effort" (see Box 2 for details on the distinction between cognitive costs and cognitive effort), with which they monitor opportunity costs associated with implementing some mental operations relative to others [26,28,29]. If continuing a task (e.g., solving a math problem) is consciously experienced as more effortful than a more attractive alternative behavior, it may motivate the reallocation of mental processing to the task that offers greater return on the invested processing (e.g., checking emails on your phone). Under this view, tasks requiring active mental effort can be costly.

Thus, at the motivational level, cognitive costs are typically regarded as negative or aversive, because they require effort [21]. Yet, conceptualizing cognitive costs as opportunity costs also suggests that the absence or withholding of actionable behaviors can be experienced as effortful and thus costly, as in the case of boredom [26,30,31], thus motivating people to play, for example, Wordle and Sudoku. In terms of sacrificed opportunity, it can be just as costly to keep the system running while it is not engaged in any valuable task as it is to continue an effortful task.

Conceptualizing cognitive costs as sacrificed opportunity, or sacrificed time and effort, has implications for how costs are measured. One direct measure of what a person is willing to sacrifice to avoid a behavior is money: it is assumed to be universally desired, relatively continuous (divisible), and commensurate across behaviors. Accordingly, in experimental work, cognitive costs have been measured by varying the rewards associated with making high-quality choices [17]. If people are responsive to differences in rewards, this is taken as evidence that the rewards of good choices are traded off against the cognitive costs of making them. Another method is to elicit the amount people are willing to pay to avoid engaging in cognitively laborious behavior [3], which can be interpreted as a direct measure of cognitive costs.

Algorithmic Costs

Another prominent conceptualization of cognitive costs focusses on the algorithmic or computational processing steps needed to implement a decision. This concept is rooted in computer science, where the "complexity" of an algorithm is described as the cost of that function, usually denominated in terms of runtime (time complexity) or working memory burden (space complexity, which is related to the notion of limited cognitive resources, see Box 1) [6]. In research on cognitive science, this idea has been adapted to understanding the costs of mental processes [7,8,32–34].

The major cost that arises from implementing several processing steps at the algorithmic level is time. Thus, algorithmic costs are typically measured in response time—the longer it takes to respond, the more processing might have been required to execute a particular algorithm and the speed-accuracy tradeoff dictates that more accuracy (or more confidence in the correct choice) comes at the cost of time. Indeed, it can be shown that computational runtime changes with the difficulty of optimization tasks [35]. For instance, recalling a memory further back in time can take longer because it requires reopening more files to find the relevant memory [36].

Another way to represent cognitive runtime or algorithmic costs is as an evidence accumulation process that drives decision making over time. Under this view, people are assumed to evaluate options by sampling noisy information either from the environment or from their internal representations, building up evidence in favor of one option over the other, before selecting the option for which net evidence reaches a predetermined threshold [37]. From this perspective, cognitive costs arise from integrating information over time to reduce the impact of noise, which may arise from imperfect perception [38], shifts in attention (in the environment or internally between memories [24,39,40]), or the stochastic nature of neural activity [41] (see Box 3 for details on the hypothesized connections between neural activity and cognitive costs). By accumulating information over time, noise is averaged out in the decision process, thus achieving a better signal-to-noise ratio. This averaging process is similar (or sometimes equivalent) to Bayesian updating with thresholds on the posterior probabilities that one or the other option is the correct choice [42–44]. Here, the cognitive costs include both the difficulty of generating useful evidence as well as the time to reach a threshold. Finally, frameworks of rational boundedness of cognition quantify cognitive costs in terms of the evidence accumulation rate, which also captures higher cognitive costs in terms of a lower signal-to-noise ratio [11,45].

Thus, conceptualizing cognitive costs as algorithmic costs (in terms of expended time during evidence accumulation) shifts the focus from the exact moment of choice to a wider timeline of cognitive processing that takes into account learning following a decision as well as processes leading up to the decision—as is the case for representational costs.

Before the Decision: Cognitive Costs When Encountering a Decision Situation

Representational Costs

Representational costs associated with a specific decision problem indicate how much of a resource a person dedicates to constructing and maintaining a representation of that problem before engaging with it. Such costs are especially salient when people get stuck in a "functional fixedness," where they cannot help representing the problem at hand in a particular way, even when other representations would be more effective [18,46–48]. Importantly, representational costs are a dynamic construct: They encompass the initial construction of a mental representation, but also the ongoing effort required to maintain and update it over time. Holding a more complex information-rich representation in mind bears a larger memory cost (e.g., remembering a credit card number vs. a postcode) and categorization rules of greater complexity are harder to learn than simpler ones [49,50]. Thus, the dynamic process of holding a representation in mind involves continually adjusting the representation as new information is received or as the context changes, which can be cognitively costly [48].

Meta-Cognitive Costs and Entry Costs

Once a problem is represented and maintained, a strategy for tackling this problem needs to be selected from available alternatives that may vary in their meta-cognitive costs. That is, algorithmic costs that have not been incurred yet but are anticipated, emerge before a decision commences, as do costs associated with identifying and selecting a suitable algorithm for the problem at hand. Research in cognitive science has suggested that such meta-cognitive costs may be learned from previous experience [51] or computed based on a tradeoff between the costs and benefits of elementary actions [7]. Yet, the computations involved in identifying and anticipating these costs are themselves costly, which has been largely overlooked in research on learned costs and resource rationality (Outstanding Questions).

Thus far we have assumed that a person is, in principle, willing to engage with a particular decision, incurring different types of costs as a consequence. Yet, in some situations, people may not engage at all and fail to represent a decision as actionable—a potential barrier that can be denominated as entry costs (e.g., not filing for tax exemptions or participating in the stock market because the activity may seem too daunting to even represent). This concept is related to task switching costs, which refer to the performance costs incurred when transitioning between tasks or contexts [47]. Task switching costs are typically studied in the context of executive control and, unlike entry costs, often involve paradigms that do not require voluntary control to switch and engage with another task (but see [46]). Thus, both meta-cognitive costs and entry costs have not been widely considered in research on cognitive costs to date.

After the Decision: Cognitive Costs Following a Decision

Although research on cognitive costs has been dominated by costs arising during a decision (e.g., in terms of sacrificed opportunities and the computational processing steps involved), many costs are faced repeatedly over time. Following each decision, the implemented decision strategy may be evaluated, and a memory trace of the incurred costs may be stored. Over repeated use of specific strategies, people may form routines or habits, which in turn reduce the cognitive costs of repeated activities [27]. They may also experience regret over engaging with a costly task, thus decreasing the likelihood of engaging with the same task in the future, or changing the way they approach the task. Thus, adopting a timing perspective underscores the notion of learning effects associated with cognitive costs over time.

Synthesis: A Timeline of Cognitive Costs in Decision Making

Integrating these diverse concepts along a timeline of cognitive costs—as illustrated in Figure 1— suggests that researchers need not select between one conceptualization over another. Rather, different aspects of cognitive costs have different cognitive consequences and a unifying principle is to consider when costs come into play. Although Figure 1 represents cognitive costs on a continuous timeline, a person may not incur all costs with each decision but can withdraw from this process at any point or decide not to enter a problem at all. For example, the appraisal of available choice strategies may reveal that the meta-cognitive costs associated with identifying viable strategies are too high to warrant action, thus leading to choice deferral after representing a problem.

Importantly, although Figure 1 treats each conceptualization of cognitive costs as separate and occurring only once across the timeline of a decision process, this is, of course, a simplification. Demarcating different conceptualizations of cognitive costs in this way aids the identification of specific intervention points for improving people's behavior—a point to which we turn next—and thus, represents a fruitful synthesis of a broad literature. Nevertheless, it is equally important to acknowledge interconnections and overlap across concepts and at different points in the timeline, and to recognize that different costs are often labeled inconsistently in the literature.

For instance, the notion of opportunity costs is intimately tied to algorithmic costs that arise from bounds in the underlying cognitive architecture (see Box 1), meaning that devoting resources to one task prevents the decision maker from performing other tasks. Critically, this sharing of cognitive resources creates an opportunity cost by preventing the parallel execution of multiple cognitive processes [52,53]. This tight connection might explain why phenomenologically aversive costs are experienced in the first place: If the deployment of cognitive resources is subjectively unpleasant, it can motivate careful use of scarce cognitive resources [26]. A similar argument can be made for representational costs, which also require computations to be upheld and thus create both algorithmic and opportunity costs. Representational costs, in turn, need to be maintained and updated over time, thus also featuring during and after a decision. Finally, identifying and evaluating strategies meta-cognitively prior to engaging with a problem as well as appraising strategies following a decision also involves computation. Thus, it could be argued that all cognitive costs—including those incurred before a decision is made and after a decision has been executed—involve elements of sacrificed opportunity and algorithmic implementation. In sum, the concepts dissociated in Figure 1 are connected in multifaceted and complex ways. Here we have placed each concept at the point in the timeline where the costs are primarily accrued and thus may most urgently require tailored interventions. Future work needs to address how these concepts and their placement on a timeline can be effectively distinguished in experimental settings.

Taking this timing perspective offers several advantages. First, it broadens the scope of research on cognitive costs to a wider timeline of cognitive processing that takes into account costs in the learning following a decision (remembered costs) as well as costs that are incurred in the lead-up to a decision (e.g., meta-cognitive costs and entry costs). Second, synthesizing conceptualizations of cognitive costs from diverse disciplines in this way facilitates cross talk between fields by identifying a common yardstick with which to regard different aspects of cognitive costs: the temporal dimension of when these costs occur in the decision-making process, and what aspects of a decision they affect. Emphasizing the timing of costs highlights how methods from different disciplines can be brought to bear on interrogating different aspects of costs [54]. At the same time, to accurately measure cognitive costs in any metric, it is essential to dissociate cognitive costs from task performance measures such as errors. Error aversion has been shown to play a significant role in task-avoidant behaviors that otherwise may appear as "effort avoidance" [30] and future work needs to ensure that cognitive costs can be successfully demarcated from similarly aversive factors (such as errors) typically involved in difficult tasks (Outstanding Questions). Finally, our synthesis offers significant leverage points for intervening on people's behavior.

Implications of a Timing Perspective for Policy and Intervention

Changing individuals' decisions is key to tackling some of the most pressing societal challenges of our day, such as climate change or health crises. We have reviewed the literature on cognitive costs with a view on individuals' decisions and the costs and impediments they face when making them. Yet, intervening on individuals' decisions and considering them in the context of broader societal issues also requires an inter-personal view on how cognitive costs unfold in strategic interactions. Take, for instance, consumer choice, where both consumers and firms engage in a variety of strategic behaviors related to cognitive costs. Consumers face an abundance of choices when selecting a product, which can make it difficult to choose [55–58], and their choices are often complicated by firms' attempts to influence their behavior to maximize profits. For instance, firms strategically influence consumers' choice architecture with the design of physical spaces and online user interfaces—as in the case of using defaults [59,60] and ordering product attributes [61]—or by increasing the cognitive costs of switching to competitors' products or services, thus creating a "lock-in" for customers [27,62]. Firms may also attempt to reduce cognitive costs for consumers to attract business, for instance, by offering personalized recommendations or product configurations to match consumer needs [63,64]. These strategic attempts to influence behavior play out at different time scales in consumers' decision process, highlighting that costs impacting behavior before a decision demand different interventions than those occurring during or after decision-making.

Table 1 summarizes classes of interventions for cognitive costs that occur at different timepoints in the decision process (see Figure 1) and provides examples for intervening on choice in different domains: from consumer choice, over personal health and financial decisions, to broader environmental considerations. By focusing on when in the decision process costs occur, our method of classification complements existing taxonomies that have grouped behavioral interventions in terms of techniques [65,66], behavioral domain [66,67], or underlying psychological mechanisms [68]. Understanding and anticipating cognitive costs allows for the reduction of barriers to effective decision-making that they impose. In adding a temporal dimension, our approach highlights how costs that impede on effective decision making can be targeted by interventions at different points along the timeline of a decision.

Table 1. How to intervene along the timeline of cognitive costs to aid decision making

	Pre Decision			During Decision		Post Decision
	Entry costs	**Representation costs**	**Meta-cognitive costs**	**Algorithmic costs**	**Opportunity costs**	**Remembered costs**
Classes of intervention strategies	Prompt representation of a problem, reduce red tape	Information control (removing extraneous information, providing representational cues and design), allow customizable design	Combat choice deferral, design choice environment (availability of options or strategies)	Offloading tools, externalized information	Incentivization, align policy and individual goals	Ensure transferability and generalizability, support routines
Example Domains						
Consumer Choice	Reduce consumer "lock in" [27,62]	Enable customized decision environment [64,76]	Influence order of product attributes [61]	Comparison matrix for products [64]	Gamification, flow [94]	Pre-selected preferred options [27]
Retirement Savings	Simplify regulations surrounding retirement plans [71]	Represent compounding nature of interest [73]	Provide suitable default options [78]	Pension calculators [88]	Tax incentives for retirement savings [90]	Set up automated payments [78]
Health Decisions	Screening/ appointment reminders [70]	Nutrition labels [74]	Promote healthy eating via school cafeteria choice environment [80]	Fact boxes communicating risks [89]	Incentives promoting health behaviors [91]	Automated reminders for yearly flu shots [70]
Sustainable environmental behavior	Recycling campaigns [69]	Carbon footprint labels [75]	Opt-out green energy plans [79]	Carbon footprint calculators [87]	Social nudges [92,93]	Provide energy consumption feedback [95]

Before the Decision Process Begins

Consider a person who fails entirely to enter or represent a decision opportunity—in their everyday thinking, they do not consider the importance of saving for retirement or making adequate health decisions. An external cue that prompts the representation of the decision problem may be an effective intervention at this stage—in the form of an advertisement, an information campaign [69], or a text message reminder (e.g., to get a flu shot [70]). Another roadblock to representing problems is red tape—people may fail to file for tax exemptions or avoid starting their own business because the involved paperwork and regulations prevent them from engaging with these financial issues [68,71].

If a person has represented a particular problem, the key consideration is whether their representation can be effectively acted upon. Accordingly, designing the decision environment in a way that helps people represent a problem effectively at a manageable cost is paramount. One tool for fostering effective representations before a decision process commences is information control, which constrains and organizes information to minimize cognitive costs through several channels [72]. First, it may be targeted at removing extraneous information to improve the efficiency of decision strategies (e.g., relying on graphic instead of text-based displays of interest compounding to improve financial literacy [73]). Second, information control may involve providing cues about the most effective representation of a problem—e.g., highlighting the importance of different pieces of information, as in the case of nutrition labels [74] or carbon footprint labels [75]. Finally, design can match a person's conventional expectations or allow them to create a personalized representation of a problem that best reflects their needs [64,76]—e.g., allowing consumers to sort products in a way that is most helpful to their decision making [77].

At the stage of meta-cognitive costs, one potential impediment is that the decision process is terminated, because the process of identifying and selecting an adequate decision strategy may seem too daunting. Accordingly, one can combat choice deferral by increasing the availability of low-cost strategies or removing non-favorable choice options from the consideration set. This can be achieved, for example, by providing an effective default option for a retirement savings plan [78], implementing opt-out green energy plans [79], or designing the choice environment in school cafeterias such that it promotes healthy food choices [80].

During the Decision-Making Process

During decision making, interventions can target either algorithmic costs or opportunity costs. *Cognitive offloading*—which introduces tools or environmental adjustments to lessen cognitive exertion—promises success in reducing algorithmic costs [81–83]. Current research on artificial intelligence and large language models offers one example of how adaptive and personalized technologies can dynamically assess cognitive load through various inputs (response times, physiological measures, behavioral patterns), and adjust their support accordingly. Although such interventions have been shown to be beneficial [84], the seamless integration of external assistance may also lead to illusions of knowledge and overconfidence [85,86], highlighting the need for careful implementation and user education. Cognitive offloading can also increase the efficiency with which decision-relevant information can be extracted from the environment. For example, providing pension calculators or carbon footprint calculators can be an effective way to outsource much of the costly mental processing involved in making sound financial or environmental decisions [87,88]. Likewise, providing effective summary formats of complex information, such as fact boxes communicating the harms and benefits of different medical options, can facilitate the cognitive processing involved in effective health decisions [89].

Interventions that target opportunity costs can be effective by shifting the balance between the cognitive costs and benefits that these costs create. A desired behavior may be directly incentivized, thus increasing the benefits of expending cognitive effort on a particular action, as in the case of implementing tax incentives for retirement savings [90] or using financial incentives to promote desirable health behaviors [91]. Opportunity costs can also be influenced through the alignment of policy goals with those of the person intended to be influenced by that policy. That is, intervening on opportunity costs may be a matter of activating existing goals—e.g., through "social nudges" that compare a person's behavior to that of a relevant social circle, such as the energy consumption of neighbors [92] and other types of environmental actions [93]. Interventions can also create goals, for example, in the case of gamification, which involves taking mechanics from videogames and applying them to influence decision-making. Gamification marketing activities, such as providing badges, for instance, create goals (i.e., accumulating achievements) and have positive effects on desirable consumer behavior [94].

The Post-Decision Phase

As people grow accustomed to similar repeated decisions, they may cache crucial pieces of information for later use by forming routines. The process of forming routines may be supported by providing feedback, for instance, about water and energy consumption [95]. Another means of encouraging effective routine formation is to highlight the value of repeated practice: For instance, consumers may form strong preferences for a particular product based on repeated experience with that product, thus reducing cognitive costs by automating future goal-activated behaviors [27]. Routines can also reduce recurring entry costs, for instance, with yearly reminders to get a flu shot [70], and established routines can be offloaded—e.g., setting up automated payments into a retirement savings plan [78] (but see [96]).

When and Why to Intervene?

In addition to explicating intervention points at different stages during the decision process, our framework allows policy makers to reverse-engineer why costs encroach on people's choices for known problems in, for example, health or savings decisions by identifying the different points when cognition is burdened. Consider junk fees, which are hidden fees and surcharges that companies add onto the prices of their products or services. Eliminating junk fees is a topical policy issue that was being investigated by the US Federal Consumer Financial Protection Bureau (see https://tinyurl.com/55jbywkn). The recognized problem with junk fees is that they are often applied after the purchase has been agreed to, which prevents consumers from avoiding them. That is, junk fees impede adequate representations of the decision problem because they obfuscate important aspects of the situation. However, another problem is that these disaggregated prices impose a heavy cognitive burden, making it difficult for consumers to evaluate past or future purchases in a computational sense. That is, while it may be possible, in principle, for consumers to deduce their best options, in practice it may be too cognitively costly for them to carry out the necessary computations. This example highlights that our framework empowers policy makers to identify several points of intervention for known impediments to people's decision making by considering when in the decision-making process costs are invoked.

Concluding Remarks

Our review highlights that cognitive costs are a multifaceted construct. Although different research communities often focus on distinct concepts of cognitive costs, many concepts can be related across disciplines by highlighting when cognitive costs come into play during the decision process. Taking this perspective, we have shown how conceptualizing a timeline of cognitive costs in decision processes offers a unifying framework that promises to generate fruitful theoretical and applied research questions. For instance, the different cognitive costs our review synthesizes may affect different people in diverse ways. Accordingly, one important question for future research is to illuminate the role of individual differences, for example, in the valuation of opportunities associated with different actions or the self-selection into or out of settings where entry costs are severe (Outstanding Questions). As such, our review facilitates theory integration across disciplines and informs policy recommendations that tackle some of the most pressing issues of our day.

Figures and Figure Legends

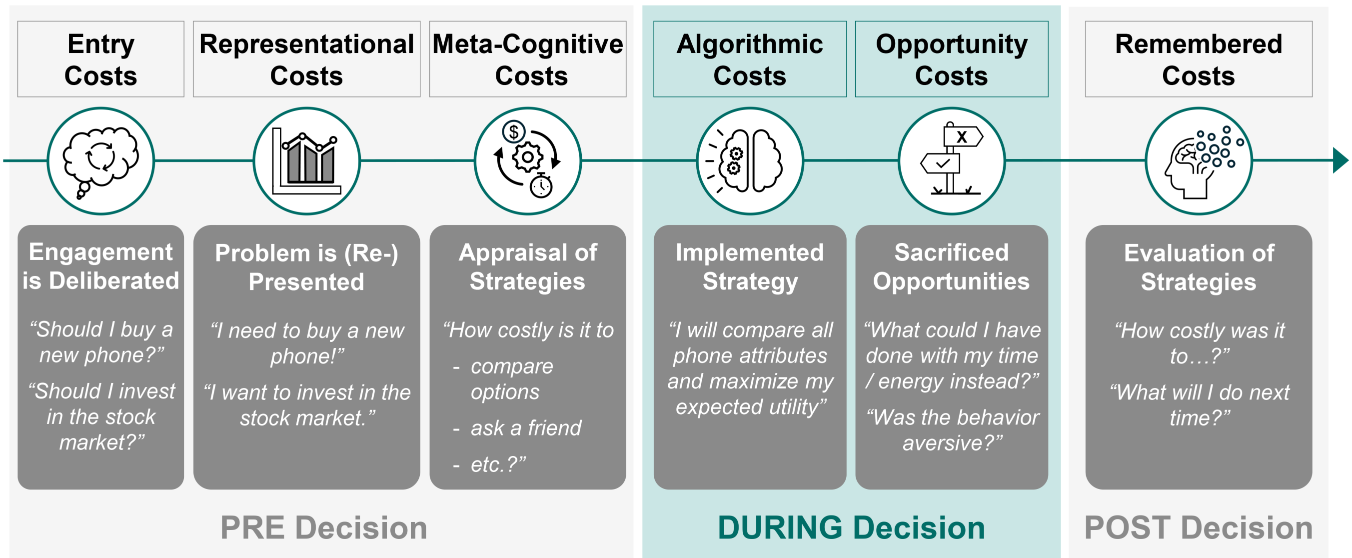

Figure 1. A conceptual timeline of cognitive costs. Consider a person pondering whether to invest in the stock market or buy a new phone. These thoughts may lead them to **enter or engage with a particular problem**, which may be costly because attention is limited and deciding to engage sets in motion a sequential process of incurring additional costs [54]. That is, the problem needs to be **represented in one way or another**, which may involve a fixed consideration set, an active search for options, or a prompt from the environment (e.g., an advert for a particular phone). Once a problem is represented, a strategy for tackling this problem needs to be selected from available strategies that vary in their **meta-cognitive costs** (e.g., evaluating phones on several attributes, weighting the importance of each attribute, and combining these calculations; asking a tech-savvy friend for a recommendation). Once a decision process commences, **algorithmic costs** unfold as an evidence accumulation

process or in the tradeoff between limited time and the desire to maximize outcomes. This decision process may be experienced as aversive or the decision maker may have preferred to do other things instead, thus also incurring **opportunity costs**. Following the decision, the person may reevaluate her decision strategy (e.g., following a friend's recommendation rather than applying a lengthy multi-attribute comparison would have resulted in the same decision at lower cognitive costs) and these **remembered cognitive costs** are fed into a learned representation which may inform future decisions by altering entry costs, representational costs, meta-cognitive costs, or forming habits.

Text Boxes

Box 1: Cognitive Costs as Limited Cognitive Resources

A complementary view to our timeline of cognitive costs posits that while mental processes are executed, they take up cognitive resources. Once resources are depleted [19] (but see [97]) or otherwise occupied [98], performance decreases. Such limits on cognitive resources are presumed to arise from constraints in the system—e.g., impaired performance in two parallel tasks suggests that these are invoking the same mental process, whereas unhampered performance indicates the tasks tax different processes [99]—which people may not have conscious control over. Cognitive resources can also be constrained willfully and people may decide whether (and how much) cognitive resources to expend for a given task. For instance, a prominent view of human decision making suggests that people's decisions are driven by simple heuristics in an attempt to reduce cognitive effort [100] at the expense of severe and systematic errors in judgment and decision making [101].

Much work has explored how such allocation of resources (or the lack thereof) can be measured and incentivized [17], and how the underlying cognitive processes unfold [7,52,53,102–106]. For instance, the concept of resource rationality suggests that cognition is guided by the optimal use of limited computational resources, meaning a rational tradeoff between the costs and benefits of using computationally sophisticated algorithms versus heuristic strategies [7,102]. Formalizing the cognitive costs involved in this process, research has decomposed heuristic strategies into units of "elementary information processes" [104]. Assuming every operation (e.g., read, compare, add) requires equal effort, certain heuristics require substantially less effort but, depending on the choice environment, may incur only a minimal reduction in accuracy [105]. That is, the concepts of bounded and ecological rationality suggest that—provided that people's cognitive strategies fit the structure of their environment—even simple, effortless strategies can lead to accurate decisions [103,107–110]. Thus, these lines of research have highlighted that to understand how cognitive costs shape human cognition, one must take account of the underlying cognitive architecture as well as the structure of the environment in which this architecture is deployed (see also [5,83,111,112]). Our framework offers the additional insight that a crucial aspect of this interaction between mind and environment is when in the decision process cognitive costs are incurred.

Box 2: Distinguishing Cognitive Costs from Cognitive Effort

To clarify and demarcate our framework from complementary concepts, it serves to define the terminologies we employ: "cognitive costs," "cognitive effort," and the phenomenological experience of mental exertion, or "sense of effort."

Cognitive effort refers to the volitional deployment of cognitive resources towards a task; in short, effort is the factor which mediates how well someone *could* perform on a task relative to how well they actually perform [20]. The positive effect of incentives on people's performance on cognitively demanding tasks [113,114] suggests that people can control how much effort they exert.

Cognitive costs refer to the timing, resource, or neuro-metabolic costs which arise from increased effort. For example, to improve one's performance in a working memory task (e.g., an N-Back task), a person needs to increase the number of items stored in working memory and promptly clear redundant items: a process which entails algorithmic costs (updating an item in working memory), representational costs (increasing the total number of items), and opportunity costs (storing one set of items precludes the storage of others), all of which may necessitate increased energy expenditure or other metabolic costs (see Box 3). Although increased effort always imposes greater cognitive costs, the inverse need not be true. For example, visual processing is both computationally and metabolically expensive [115], yet it is not a process considered "effortful."

Related to both cognitive effort and cognitive costs is the phenomenological experience during mental tasks ("sense of effort" [116]). The psychic pains endured during unrewarding cognitive tasks are familiar—

think tax returns and other administrative drudgery. Similarly, the greater the effort required by a task, the greater the cognitive costs incurred, and the more aversive the task typically feels. Although higher cognitive costs typically entail a greater sense of effort, there are circumstances under which the two are divorced. For example, if a task is intrinsically rewarding—e.g., crossword puzzles, video games, reading—it may evoke pleasurable "flow" states [117] and allow for greater performance without an increase in negative affect. In such cases, the attained rewards presumably offset the cognitive costs incurred due to increased effort exertion. While related, cognitive costs, and people's "sense of effort" are distinct and are therefore worthy of clear characterization.

Box 3: Neurobiological and Metabolic Costs of Cognition

Neurobiological accounts can be placed into three camps: depletive, accumulative, and limited bandwidth. Depletive accounts propose that increases in neural activity (via the volitional exertion of mental effort) lead to quantifiable decreases in metabolic resources. In the same sense that physical exercise depletes glycogen, cognitive effort is assumed to entail metabolic costs. Early theories proposed that blood glucose was depleted [118]. Such accounts, however, failed to observe reliable relationships between effort exertion and changes in blood glucose [119,120] and it remains unclear why metabolic resources would be depleted by cognitively demanding tasks but not tasks such as vision that are equally (or more) computationally expensive yet are not experienced as costly [8]. Moreover, these theories struggle to account for the beneficial effects of physical exertion—which is demonstrably resource intensive—on cognitive performance [121] and cannot easily accommodate evidence suggesting the brain's total energetic costs barely differ between activity and rest [122–124]. Thus, the depletion account faces serious challenges [15].

Accumulative accounts posit that the costs we feel during mental exertion are the result of the build-up of neurotoxic byproducts. Recent work found that prolonged bouts of mental exertion (e.g., performing a working-memory task for 6 hours) led to increases in glutamate deposits in the lateral prefrontal cortex [125]. Additional work is required to establish whether glutamate deposits reliably increase during different mentally demanding tasks and whether these increases are enough to be considered neurotoxic [126]. Beta-amyloid proteins, which are a primary cause of Alzheimer's disease [127], have also been linked to the costs of effort and control [128]. Although plausible, there is currently no empirical evidence establishing a link between increased neuronal activity and beta-amyloid deposits (Outstanding Questions).

Limited bandwidth theories [11] account for the brain's stable total energy expenditure while highlighting that increases in neural activity in one region lead to decreases in activity for parallel regions. A some would argue that we think at only 10 bits/s [129], it is important to use those bits wisely. In this view, cognitive costs index the metabolic expenditure of a particular process and its circuitry relative to the brain's total output, as opposed to measuring the absolute metabolic burden of a particular cognitive task.

Cognitive computations are undoubtedly dependent on the supply of metabolic fuel. Yet it remains unclear whether theories at the implementation level of analysis [130] wholly account for the costly nature of cognitive effort.

Memorandum

In memory of Gerald Häubl whose passion for the interdisciplinary study of human decision making will continue to inspire us.

Declaration of Interests

The authors declare no competing interests.

Resources

Consumer Financial Protection Bureau (2024) *CFPB Highlights the Hidden Costs of Health Savings Accounts*. https://www.consumerfinance.gov/about-us/newsroom/cfpb-highlights-the-hidden-costs-of-health-savings-accounts/

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