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A Generalizable Framework for Assessing the Role of Emotion During Choice

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The study of emotion has been plagued by several challenges that have left the field fractionated. To date, there is no dominant method for measuring the nebulous and often ill-defined experience of emotion. Here, we offer a new way forward, one that marries numerically precise measurements of affect with current models of human behavior, to more deeply understand the role of emotion during choice, and in particular, during social decision-making. This tool can be combined with multiple other measures that capture different features and levels of the emotional experience, making it particularly flexible to be used in any number of contexts. By operationalizing the classic circumplex model of affect so that it can deliver fine-grained, continuous measurements as affect evolves overtime, our goal is to provide a generalizable and flexible framework for computing affect to infer emotions so that we can assess their impact on human behavior.

Public Significance Statement
Given the state of research on emotion, it is imperative that decision researchers embrace affective measurements that can provide rich, continuous observations that will serve as a common foundation across paradigms, contexts, and psychological questions. By harnessing technological advancements that enable researchers to formally compute affect in real time, we have the potential to revolutionize our understanding of emotions and their impact on choice.

Keywords: emotion, affect, decision-making, dynamic

In 2014, Jon Lester was the starting pitcher for the Boston Red Sox and an All-Star Game player who had just pitched his team to a World Series title. Lester had been an integral part of the Red Sox winning multiple championships, and now his current contract was coming to an end. In negotiating a new deal, the Red Sox offered Lester a paltry $70 million, less than half the packages of other comparable pitchers. Lester was so offended that he shut down all subsequent negotiations and went on the open market, where he subsequently signed a deal with the Chicago Cubs for more than twice that, cashing in on a $155 million windfall (Shaughnessy, 2014). Although Lester expected a reasonable contract from his beloved hometown team, his surprise and emotional reaction to the low-ball offer changed his priorities and led him to cut all ties with the franchise to which he had been loyal for more than a decade. What aspect of Lester's emotional experience drove him to make that decision?

Emotional reactions are part and parcel of our everyday social lives. Whether we are confessing our feelings to a romantic partner, telling a friend an uncomfortable truth, or working out how to resuscitate a damaged reputation, emotions drive our beliefs (Paulus & Yu, 2012; Saxe & Houlihan, 2017), desires (Loewenstein, 1996), and goals (Bagozzi & Pieters, 1998; FeldmanHall & Chang, 2018; FeldmanHall et al., 2015). Despite emotion's importance to the inner machinations of human social life, the study of emotion has been plagued by several challenges that have left the field fractionated. For decades, a debate raged over how researchers should define emotion, one that continues to this day (Barrett et al., 2016; Izard, 2010; Plutchik, 1989; Scherer, 2005). There have also been skirmishes about how to best

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measure emotion, which means that there is no dominant method for translating the nebulous and often ill-defined experiences of emotion that transpire in the wild into something that can be formally quantified in the lab (Mauss & Robinson, 2009). Although there has been a recent growing interest in characterizing emotion—dubbed the rise of affectivism (Dukes et al., 2021)—many open questions have been left unanswered regarding the role of emotion during social learning and decision-making processes.

Here, we offer a new way forward, one that marries numerically precise measurements of affect with current models of human social behavior. Given the many decades of thoughtful and elegant work dedicated to measuring emotion (Mauss & Robinson, 2009), we suggest modernizing one of the most reliable and well-vetted tools in the field—the affect grid (Posner et al., 2005; Russell et al., 1989)—rather than reinventing the wheel from scratch. By updating and revising the affect grid so that it can deliver fine-grained, continuous measurements as affect evolves overtime, our goal is to provide a generalizable and flexible framework for computing affect to infer emotions that are compatible with behavioral assays of human behavior. In other words, we propose a method that can overcome many of the challenges faced by the field over the years to advance our understanding of emotion's role in decision-making.

Emotion's Turbulent Past

The paradoxical nature of emotion is that, on the one hand, everyone has an intuitive understanding of it (i.e., folk theories of emotions; Johnson-laird & Oatley, 1992), but after many decades of theorizing and scientific debate (now spanning more than a century), there is little consensus about how to precisely define emotion (Barrett et al., 2016). There are three main eras of the scientific examination of emotion—the "Golden Years" (1855–1899), the "Dark Ages" (1900–1959), and the "Renaissance" (1960s–present; Gendron & Barrett, 2009)—that together have contributed to this lack of consensus, and indeed have spurred heated quarrels over what we mean when we use the term "emotion."

The Golden Years laid the groundwork for many modern approaches to emotion, including developing the theory of basic emotions, which was inspired by Darwin's early observations (Darwin, 1872). Basic emotions are considered special kinds of biologically driven responses triggered by objects and events in the world (Tomkins, 1962). The adjective "basic" is meant to communicate two important features of the theory: that there are certain emotions that differ from each other in critical ways, and that these specific emotions evolved to serve an adaptive role for survival (Ekman, 1992). While the proposed number of basic emotions seems to be growing (e.g., Cowen & Keltner, 2017), most emotion theorists recognize six key emotions that serve as the core foundation. These six emotions—anger, fear, happiness, sadness, disgust, and surprise (Ekman & Friesen, 1971)—are distinguished from other affective phenomena because each is thought to have unique features regarding its visible signals, its physiology, and the events that proceed them. For example, anger commonly elicits a unique combination of lowering the brow while simultaneously raising and tightening the upper lip (Ekman & Friesen, 1978). Although there are other emotions that are not part of this set (e.g., rage, frustration), they exist under the hood of one of the basic emotions (e.g., anger) and are sometimes called secondary emotions (Ekman et al., 1987) or are otherwise assumed to be combinations of the basic six (Du et al., 2014; Ortony & Turner, 1990). Researchers have documented that people from disparate cultures who do not share a common language, social norms, or expectations of emotional response can reliably classify all six basic emotions from photographs of prototypical emotional facial expressions (Matsumoto et al., 2008). This is taken as good evidence that these emotions act as a common thread that runs through all cultures in every corner of the earth, a proverbial call for the universality of emotions (Ekman et al., 1972). Although the validity of this result has recently been questioned (Barrett et al., 2019; Nelson & Russell, 2013; Russell, 1994), many researchers in the basic emotion camp still argue that these six emotions are biologically distinct, are produced by dedicated circuits within the brain, and are shared among everyone.

After years of basic emotion research, the field fell into the Dark Ages, during which relatively little research was devoted to characterizing the human emotional experience (with notable exceptions; see Gendron & Barrett, 2009). The so-called Dark Ages can be largely attributed to the rise of Behaviorism, a theory (and era) that prioritized bypassing any "intermediate" feelings or states of the mind by focusing directly on the physical causes of behavior (Skinner, 1974). Behaviorists viewed emotions as epiphenomena—mere byproducts of environmental conditioning—which, to use Skinner's own words, "have no explanatory force" (Skinner, 1975). During this time, experimenters began observing physical changes in the body, face, and behavior, which varied across subjects, and these recorded observations led researchers to start questioning the founding tenets of basic emotion theory. In short, the inability to find discriminable responses (in the face, body, and behavioral outputs) for each, compounded with behaviorism's dismissal of emotions, meant that few models of emotion were considered during this time.

The lull in interest in emotion has been replaced by a new, far more industrious chapter, the Renaissance, which has been blooming and flourishing since the 1960s. In direct contrast to the work on basic emotions and building off some of the observations collected during the Dark Ages, researchers began to think about emotions not as innate, universal, or biologically hard-wired, but instead as constructed and appraised through experiences (Arnold, 1960; Frijda, 1993; Reisenzein, 2006). One watershed moment for understanding the structure of emotion was Schachter and Singer's seminal experiment, which revealed that emotions gain their significance as a result of cognitive appraisals (Ellsworth, 2013; Schachter & Singer, 1962). In their experiment, participants were given epinephrine (adrenaline), a hormone that increases arousal by increasing heart rate and blood pressure, and only some participants were informed about these side effects. Those who were informed had a cognitive explanation for their heightened arousal, whereas the uninformed participants' unexplained arousal increased their susceptibility to interpreting their bodily feelings as emotions that stemmed from their own experiences (i.e., either anger or euphoria, depending on how others around them were behaving). This led Schachter and Singer to propose a two-factor theory of emotion, where emotional states result from an interaction between physiological arousal and the cognitive interpretation of that arousal.

Just as Schachter and Singer focused on cognitive appraisals of arousal, other researchers have considered emotion as an interpretation about a range of subjective bodily feelings, including arousal, which is often referred to as affect (Russell, 1980, 2003). In particular, core affect comprises consciously accessible feelings that are often related to bodily responses (e.g., beating heart) and elementary subjective feelings free of any implied cognitive structures (Barrett & Bliss-Moreau, 2009; Russell, 2003), and is typically measured along a pleasure/displeasure (valence) dimension and an intensity (arousal) dimension (Russell, 2003). Relatedly, other modern perspectives argue that emotions emerge from applying one's social and cultural knowledge to one's subjective bodily feelings (Barrett, 2011; Panksepp, 2007), a related theory of emotion known as the constructivist view. Factor analyses of self-reported feelings reveal that discrete emotions (e.g., anger, sadness, happiness) vary within these two dimensions (Russell & Barrett, 1999). Unlike early appraisal theories that argue any affective evaluation is axiomatic to the experience of emotion, constructivist approaches focus on the basic cognitive or psychological building blocks (e.g., linguistic or social knowledge) that allow a person to evaluate their affective reactions (Barrett et al., 2007; Barrett, 2011; Lindquist et al., 2006). However, the time spent detailing the nuance of how these taxonomies of emotion are constructed has left scientists spinning their wheels working toward a formal definition without actually progressing the field forward (Barrett, 2006; Barrett et al., 2015).

Although to this day, the field struggles to establish a definition of emotion that would satisfy most emotion researchers, an important distinction that did arise from this work on appraisal and constructivism—and the many debates that ensued—led to an important distinction between the terms "emotion" and "core affect" regarding how they should be used and understood by scientists (Dixon, 2012; Russell & Barrett, 1999; Wundt, 1903). In modern-day emotion research, most affective scientists would agree that the term "emotion" is typically used to refer to a certain set of (mostly) conscious feelings that can be labeled, such as sadness (Izard, 2010; Lambie & Marcel, 2002; Schiller et al., 2022), whereas core affect is a subjective emotional experience defined predominantly along arousal (intensity) and valence (pleasantness) dimensions.

The Relationship Between Emotion and Choice

How do emotion and affect influence choice? Had the All-Star pitcher Lester been less angry (or annoyed, or disappointed, or …), he might have countered the low-ball offer instead of leaving the Red Sox for the open market. Operationalizing the role of affect and emotion during learning and decision-making is critical for better understanding the mechanisms that guide human behavior (Phelps et al., 2014). In the last few decades, researchers have begun to merge the study of emotion with the study of judgment and decision-making (Lerner et al., 2015; Loewenstein et al., 2001; Loewenstein & Lerner, 2003; Rick & Loewenstein, 2008). This research, which has largely stayed within the purview of economics (a field that for many decades rarely, if ever, mentioned emotion or affect), has long been consumed by the dual systems theory of cognition (Evans, 2009), which argues that there are two processes in the brain (and mind) that control behavior: one that is rapid, automatic, and effortless, and the other that is slow, sequential, and controlled, which roughly maps onto emotion and reason, respectively (Kahneman, 2011).

This singular focus has limited progress toward understanding the distributed and dynamic nature of emotion during human behavior and instead has led to an oversimplification of the impact of emotion on choice (Van Bavel et al., 2012). To illustrate, early on, the focus of decision-making research was to identify how people relied on simplified cognitive strategies called heuristics (e.g., the availability and representative heuristics) to make choices (Tversky & Kahneman, 1974). During this time, affect and emotion were largely overlooked as motivators. It was not until the turn of the next century that the role of affect became recognized in the field of judgment and decision-making and was promptly labeled the "affect heuristic" (Slovic et al., 2007), which described how affect can be used as a mental shortcut to lead us astray. These studies combining judgment and affect would lead subsequent researchers to search for a broader framework that could explain the mechanisms governing cognitive and affective mistakes.

The popularity of the dual system theory led many researchers to posit that the automatic system causes errors during judgment and decision-making (Haidt, 2001; Johnson & Tversky, 1983). The litany of evidence documenting these "error-prone choices" was rebranded as "affective impulses" (Figner et al., 2009), giving many the impression that emotional responses cause people to deviate from normative or "rational" choices. This is neatly demonstrated in one of the most widely used economic games, the Ultimatum Game (Güth et al., 1982). In the classic version, participants are paired up, and one person is made the Proposer and endowed with an amount of money (e.g., $10). The Proposer then makes a monetary split with the other participant, the Responder, who can either accept the offer as is or reject it. Rejecting results in both players receiving nothing (essentially, a form of costly punishment). The normative framework suggests that rejections are irrational as receiving even a small amount of money should be considered more valuable than receiving no money. However, across numerous studies that span time and cultures, people consistently reject unfair offers (Henrich et al., 2001), a result that has been chalked up to emotion (Civai et al., 2010; van Winden et al., 2008; Yamagishi et al., 2009).

One of the most popular theories explaining these rejections is the "wounded pride/spite model" (Pillutla & Murnighan, 1996), which states that unfair treatment evokes a negative emotional reaction, such as anger, which in turn causes people to reject the offer. However, evidence for specific emotional experiences like anger has only been indirectly implicated through reverse inference (Sanfey et al., 2003), or studied in isolation without probing other similar emotional experiences (Fehr & Gächter, 2002). Studying anger in isolation is problematic because interrogating how much anger a person feels may artificially impose an expectation that the person *ought* to feel anger, and it does not allow participants to report any other emotional experiences they may be having. In an attempt to find a more direct link between anger and decisions to reject, subsequent studies focused largely on mood inductions using emotionally evocative videos. Compared to neutral or happy videos, both sadness (Harlé & Sanfey, 2007) and disgust (Moretti & di Pellegrino, 2010) increased rejections of unfair offers. While at first blush, these results present a promising lead toward clarifying how specific emotions guide decisions to punish, it is possible that in the real world, *any* negative feeling might be sufficient to prompt people to punish (Liu et al., 2016). Like with much of emotion's inchoate past, a lack of a generalizable framework has impaired the field from making progress toward understanding how affect, in general, drives social decision-making.

The Challenges Associated With Measuring Emotion

Because emotion and affect are, by definition, subjective experiences, it has been an enduring challenge to precisely measure them. Typically, the field has relied on three broad methods that are believed to capture variations in the magnitude of an emotional experience (Plutchik, 1989): subjective reports (often using Likert scales, such as "how angry do you feel?"), peripheral visceral signals (recording skin conductance, heart rate fluctuations, brain activity, or pupil dilation), and facial expressions (documenting muscle activity in the face). Mood checklists, for example, are a common way of measuring specific emotions, where participants are asked to select one (or more) adjectives (e.g., calm, joyful, disappointed), which best describe their immediate, subjective feelings. These direct and straightforward measures have the advantage of capturing a person's immediate self-reported emotions, and they have been used to uncover the emotions experienced in everyday life (Trampe et al., 2015), and even to illuminate the structure of emotion concepts (Cowen & Keltner, 2017). However, one of the strongest challenges to measuring emotions in this way, or even asking about a particular emotion on a continuous Likert scale, is that emotions are rarely homogeneous and are more varied than a limited checklist (anger can feel and look very different both within a person and between people). Indeed, thousands of semantic terms exist for describing feelings. Self-report checklists contain only a fraction of these (e.g., Positive and Negative Affect Schedule; Watson et al., 1988) and are often specialized to researchers' specific interests, which highlights a major constraint: When researchers select a set of emotion terms, they limit the generalizability of their results.

While autonomic physiological activity and observable facial changes sidestep some of these issues, they come with their own problems. The general consensus is that brain and bodily responses are an essential part of the emotional experience that bias behavior (Bechara & Damasio, 2002; Naqvi et al., 2006). However, the tools we have to measure many of these peripheral bodily responses often capture only one affective dimension—arousal—and there is no comparable metric that can measure how the body indexes pleasure (although blood oxygenation level dependent activation reflects hedonic pleasure of rewards; Haber & Knutson, 2010). Because fluctuations in physiological arousal are regulated by the autonomic nervous system, researchers have searched for physical signatures of emotion using pupil dilation (Bradley et al., 2008), skin conductance (Christopoulos et al., 2016), and heartrate (Lang et al., 1993) metrics. Although the relationship between these physiological responses and emotions has not been fully characterized, attempts to use these measures as an "emotional fingerprint" have been met with criticism and are considered largely unsuccessful (Siegel et al., 2018). Second, some of these visceral bodily responses are too slow to allow quick responses to the environment (i.e., skin conductance response follows the same sluggish response seen in fMRI, where it takes up to 16 s to elicit a response; Cannon, 1927; Quigley & Barrett, 2014). This can be a problem when trying to record arousal responses during a social interaction in which there are rapidly evolving tensions.

Because almost every facet of social interactions involves signaling and interpreting emotions through the face, facial expressions have long been considered the window to understanding the human emotional experience. Under the assumption that facial expressions must be adaptive and subject to evolutionary pressures (Darwin, 1872; Schmidt & Cohn, 2001), researchers have taxonomized facial muscles and speculated about their functional roles. The facial action coding system (FACS) is the main research tool that breaks facial expressions into individual components of muscle movements called action units (Ekman et al., 2002; Ekman & Friesen, 1978). Recommendations about how to define emotion-specific expressions from FACS are few and far between (e.g., Ekman & Rosenberg, 2005), and meta-analyses for implementing FACS to study emotion show large inconsistencies and reporting biases (Clark et al., 2020). Furthermore, extensive research has documented weak reliability and specificity (Barrett et al., 2019) and wide variability in action unit combinations when signaling emotions across cultures (Jack et al., 2009, 2012), which ultimately suggests that facial expressions may be less informative than simply knowing the context in which the emotion arises (e.g., being cornered by a bear; Carroll & Russell, 1996). While facial movements have some useful information, they lack the generalizability necessary to be a robust measure of emotion for decision sciences (Aviezer et al., 2012).

A Revised Tool for Measuring Emotions: The Dynamic Affect Grid

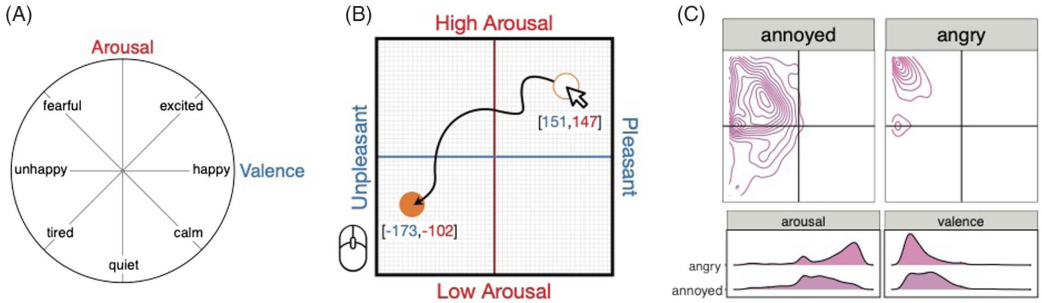
Of course, no one tool can overcome all the challenges associated with measuring emotion or affect given their subjective and heterogeneous nature, and arguably, there may never be a gold standard measure of emotion. However, we maintain there is one tool in particular that can provide a strong foundation for measuring emotion. This tool mitigates many of these concerns over measurement (thus sidestepping the debates that have plagued the field for decades) to offer a precise and mathematical approach for measuring affect. In conjunction with behavioral assays, it can be used to infer the nature of emotions in ways that allow results to be generalized.

Categorical scales, physiological responses, and facial expressions are limited because they cannot capture subjective feelings that do not fall into predefined categories or are too slow to capture rapid changes in affect experienced in naturalistic contexts. The affect grid measure, however, which was first proposed by Russell and colleagues in the late 1980s (Russell et al., 1989), proved to be a simple but elegant way to capture conscious subjective feelings in a quick, single-item measurement. The original scale was a 9-by-9 grid, demarcated by a horizontal axis representing an unpleasant–pleasant (i.e., valence) dimension and a vertical axis representing a low-to-high arousal dimension. These underlying dimensions—which comprise core affect—represent the basic ingredients to generate an emotion, and extensive study of how different emotions relate to one another (using statistical techniques such as multidimensional scaling) has repeatedly yielded a two-dimensional model, often referred to as the circumplex model of affect (Posner et al., 2005). The affect grid measure has been particularly influential in research on emotion and has been widely used to validate affect inductions (Lindquist & Barrett, 2008), assess what features of the world produce emotional reactions (Holbrook & Gardner, 1993), and how people move through affect space during their daily emotional experiences (Kuppens et al., 2007).

Measurements of core affect (Figure 1A) can assess an individual's feelings toward a variety of objects or situations (Russell, 2003). A person who is feeling angry might, for example, report high arousal and negative valence by rating their emotional state in the upper-left corner of the grid. Combining the affect grid with any type of instruction (e.g., "Rate your mood right now" or "How do you feel about X") makes it particularly flexible so that it can be used in any number of laboratory contexts. In fact, it can even be adapted for nonverbal, graphical visuals (Bradley & Lang, 1994). In addition, the partitioning of affect along these two dimensions of valence and arousal is also reflected by the physiological responses emitted from the body and the organization of the brain regions that encode affect (Duncan & Barrett, 2007; Kensinger & Schacter, 2006; Lang et al., 1993; Phan et al., 2003), which suggests that this scale is an exceptionally appropriate format for capturing how humans experience subjective feelings.

Although this simple and quick-to-implement scale has been used widely in the past 30 years, and there is now a large body of research showing its validity and reliability (Killgore, 1998; Russell et al., 1989), its original instantiation only affords researchers a coarse, low-dimensional, and absolute measurement of affect. If the affect grid were to be combined with contemporary methodologies, however, it would enable this single-item scale to be widely used across a number of contexts, a tool that could be leveraged to generate a flexible and generalizable framework for studying affect and emotion in vivo. To modernize the affect grid—which we term the dynamic affect grid (DAG)—so that it is compatible with a number of cutting-edge scientific methods, a few simple revisions are necessary. First, the sampling resolution of the grid should be increased substantially to enable precise, fine-grained measurements of affect, which allows the grid to capture changes in affect that occur on a more granular and continuous level. Although any increased sampling resolution would work, in our own research, we have used a sampling resolution of 500×500 pixels, which facilitates a far more fine-grained measurement than the original 9×9 pixelation (Heffner et al., 2021; Heffner & FeldmanHall, 2022). In our own data sets, unpublished analyses reveal that down sampling to a lower resolution (e.g., 100×100) makes it more difficult to distinguish between emotions. In a high-resolution grid, participants report their affect by clicking anywhere in the space, which means that their subjective feelings are recorded in a low-dimensional coordinate $[x, y]$ space (Figure 1B).

Figure 1
Operationalizing Core Affect: The Dynamic Affect Grid



Note. (A) The circumplex model of affect shows how discrete emotions fall along valence (unpleasant–pleasant) and arousal (low–high intensity) dimensions. (B) The dynamic affect grid (DAG) is a 500–500-pixel grid given to participants to rate their affective experience over time. Mouse tracking can be implemented to capture the transition dynamics as a person moves between affective states. (C) 2D and 1D density plots of affective ratings for the words "annoyed" and "angry." Panel C is adapted from "A Probabilistic Map of Emotional Experiences During Competitive Social Interactions," by J. Heffner & O. FeldmanHall, 2022, *Nature Communications, 13*(1), Article 1718, p. 5 (https://doi.org/10.1038/s41467-022-29372-8). CC BY. See the online article for the color version of this figure.

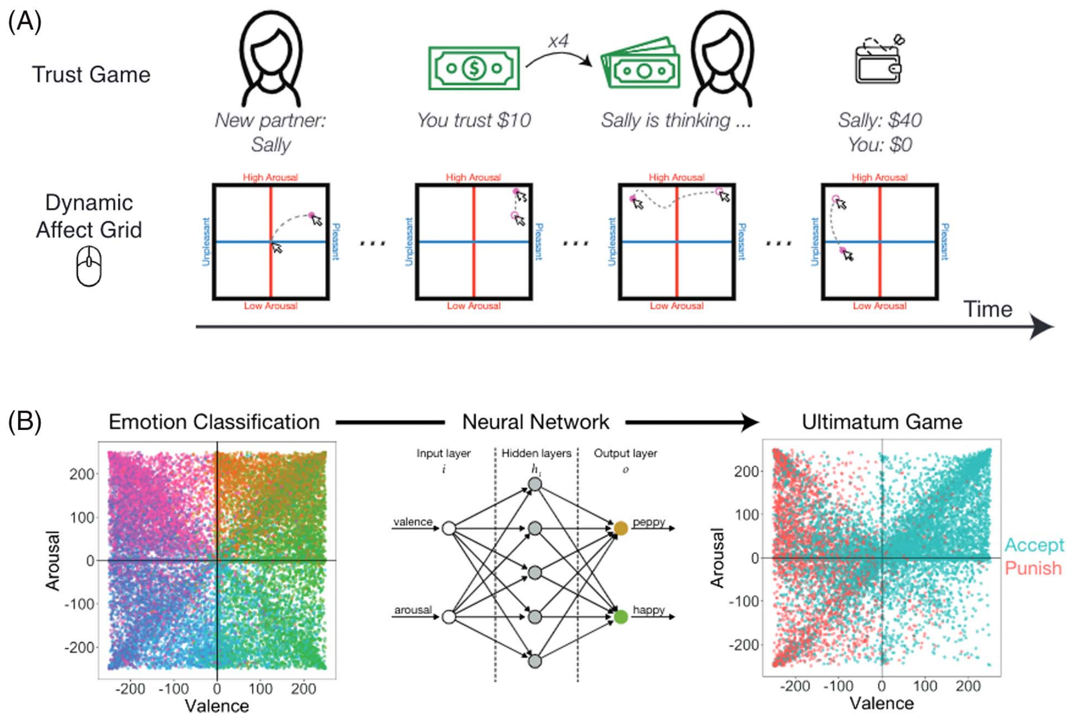
Second, this more fine-grained affective measurement can then be leveraged to mathematically quantify affect (or even emotion) at multiple different levels of analysis, situating it as a flexible tool that can be used across paradigms and contexts. For example, this measure allows us to jointly capture group-level differences between discrete emotions such as anger, which is more unpleasant and intense than annoyance (Heffner et al., 2021), while also using density analyses to describe how anger is less variable at the population level than annoyance (Figure 1C). These group-level data can then be combined with more sophisticated statistical pipelines to figure out *which* emotion a person might be experiencing, without ever directly asking about a specific emotion (thus avoiding many of the issues that go hand-in-hand with demand characteristics; Heffner & FeldmanHall, 2022).

Third, to capture the temporal dynamics of emotion rather than simply query the final emotion rating as is commonly done, researchers can either deploy the DAG multiple times within a trial to compute differences in affect, or use continuous affective ratings (Figure 2A). One way this can be implemented is by using mouse-tracking software (which is easily implementable in many programming languages) to record an individual's cursor as it moves across the affect grid (Hutcherson et al., 2005), thus measuring the dynamic nature of affect as it unfolds overtime. By sampling where the cursor is at any given moment (e.g., as the cursor moves across the grid, different [x, y] coordinates can be recorded every 10 ms), a person's affective experiences and any associated temporal trajectories can be continually documented. This method powerfully allows researchers to explore how affect fluctuates over time in a uniform space without predefined categorial boundaries or discontinuities (especially if the DAG is implemented without an axis or grid demarcations). This technique has been recently deployed (Belfi et al., 2019) to (a) make claims about how swiftly affective experiences bias choice (Heffner et al., 2021), (b) to document how affective states of unseen persons can be identified from context alone in naturalistic conditions (Chen & Whitney, 2019), and (c) to understand how personality and emotion dispositions shape dynamics of affect longitudinally (Kuppens et al., 2010). For example, in our own work (Heffner et al., 2021), we used mouse tracking to capture the affective trajectories of participants as they received unfair offers in the Ultimatum Game. We demonstrated that subsequent choices to forgive or punish an unfair partner can be predicted early on in the participant's valence trajectory, well before participants were able to report how pleasant or unpleasant they actually felt about the offer.

As Russell originally demonstrated in 1989, participants can be quickly trained to use the DAG by first thinking about how to classify specific emotions, such as anger, happiness, sadness, disgust, and so forth, on the grid. After brief instructions on how to use the grid, researchers can present participants with a list of emotions. For example, a participant might be asked to use their cursor to rate the label "excited" from their memories or knowledge of that word. One advantage of this approach is that comparisons between specific emotions can be quickly inferred without having to do a pairwise comparison of similarity ratings (e.g., how similar are excited and happy; Posner et al., 2005). The pairwise comparison method can take a while depending on how many emotions are presented (e.g., 20 emotion words require 190 pairwise combinations to be presented). In contrast, using the DAG, researchers can simultaneously see how the emotion "angry" compares to the emotions "surprised," "excited," "annoyed," and so forth. While the point has been made that pairwise comparisons are capable of capturing more nuance (e.g., how the set changes similarity ratings; Kriegeskorte & Mur, 2012), the DAG offers researchers

Figure 2

Integrating the Dynamic Affect Grid With Decision-Making Paradigms



Note. (A) The dynamic affect grid (DAG) can be combined with virtually any decision-making paradigm. In this case, we illustrate how the DAG can be merged with a classic economic game called the Trust Game. (B) The DAG can also be leveraged to create a probabilistic map of emotion to classify which specific emotions are experienced during certain social interactions, such as when someone behaves unfairly in the Ultimatum Game. Panel B is reprinted from "A Probabilistic Map of Emotional Experiences During Competitive Social Interactions," by J. Heffner & O. FeldmanHall, 2022, *Nature Communications, 13*(1), Article 1718, p. 3 (https://doi.org/10.1038/s41467-022-29372-8). CC BY. See the online article for the color version of this figure.

a rapid tool that quickly and effectively captures most affective experiences. In short, by updating the classic affect grid to incorporate granular affective measurements that can be assessed in a temporally continuous manner, the DAG provides a relatively low-cost tool to precisely assess fluctuations (or changes) in affect over time.

A Generalizable Framework for Measuring Affect During Decision-Making

Merging the DAG With Existing Decision-Making Paradigms

The beauty of the DAG is that it can be merged with other paradigms to more deeply explore the relationship between affect (or emotion) and choice. If we hark back to the seminal work investigating economic games and emotion, researchers either combined games with reports of specific emotions (i.e., "how angry do you feel after receiving an unfair offer in the Ultimatum Game?") or simply inferred the presence of a particular emotion from physiological responses (Sanfey et al., 2003). The DAG not only sidesteps the issues with these existing measurements but also can be inserted particularly easily into existing paradigms, rendering it an especially flexible tool. Imagine for a moment having participants record affective experiences continuously with the DAG while watching a movie or while participating in an economic game (Figure 2A). In either case, the DAG can be used to answer a number of outstanding questions about human cognition and behavior. For example, by continuously reporting on either one's own affective experiences or the inferred affective experiences of another, researchers can better characterize how our own affective experiences diverge from how we perceive the affective experiences of others. While the gap between self and other is fairly well researched in other domains (FeldmanHall et al., 2014; Hutcherson et al., 2015; Jackson & Decety, 2004; Kuiper & Rogers, 1979), much less is known about how the structure of affective experiences differs between self and other (although see Batson et al., 1991; Preckel et al., 2018).

The DAG can also be used to measure the speed or velocity of certain affective trajectories, which would enable researchers to infer how quickly certain affective experiences come online (Freeman et al., 2011), or to probe which parts of the affect grid are most potent in biasing choices. Combining the DAG with advanced mouse-tracking techniques (Hehman et al., 2014) would enable researchers to quantify *when* participants change their affective ratings. This could be done by measuring any sharp changes in the mouse's velocity as it moves across the affect grid (i.e., sudden movements in the opposite direction). The DAG can even be merged with existing models of human behavior, such as the drift-diffusion model (DDM), which is a model of sequential sampling in which the decider accumulates enough evidence to make a decision (Ratcliff & McKoon, 2008). The DDM describes behavioral performance (i.e., choice and reaction times) across a whole range of tasks, and if combined with the DAG, it could be used to quantify affective goal states or the conflict between competing emotions. Researchers could examine how evidence accumulation parameters from the DDM (e.g., threshold, drift) might be modulated by changes in real-time valence and arousal ratings. Indeed, there is strong evidence that heightened arousal increases variability in evidence accumulation rates (Murphy et al., 2014), although less is known about how changes in arousal and valence affect cognitive processes. In short, the DAG could be combined with any number of existing decision paradigms (e.g., behavioral economic games, multi-attribute choice paradigms, or reinforcement learning tasks). This would allow researchers to develop a unifying framework for studying affect that not only provides an unprecedented level of temporal granularity but also is insensitive to task context, thus enabling results to be linked across many levels of analyses.

Using the DAG to Answer Open Questions About the Relationship Between Emotion and Choice

There are multiple different questions pertaining to emotion that can be answered by deploying the DAG within human decision-making paradigms. For instance, we still do not understand which emotions motivate certain choices (i.e., the coupling between emotion specificity and decision contexts), in part because of the methods and statistics often used to study emotion and choice. However, if the DAG is implemented within a task, it can also be combined with different statistical pipelines to clearly document the relationship between core affect, emotion specificity, and choice. For example, we recently combined several machine learning algorithms (i.e., neural networks) with the DAG in order to create a probabilistic map of emotion that could be used to classify which specific emotions are experienced during certain social interactions (Figure 2B). First, we embedded the DAG in a series of behavioral economic games, and thus had a large set of unlabeled affective data collected during these social interactions that could be classified into specific emotion categories. We then used labeled affective ratings taken from an emotion classification task (described above) to train supervised machine learning algorithms to classify the probability of a specific emotion occurring given a set of valence-arousal coordinates. By combining the emotion classification task with the data from the unlabeled affective data from the economic games, we were able to reverse engineer which emotion a person was likely feeling (e.g., anger, sadness) when they decided to punish an unfair transgression (Heffner & FeldmanHall, 2022). Results revealed that the argument that anger motivates punishment could not explain people's motivations to punish; instead, it appears that a diverse array of negative emotions, such as disappointment or sadness, are far more likely to motivate people to punish another for behaving unfairly.

There are other open questions about emotion that can be answered by combining the DAG with existing paradigms and new statistical methods. For example, can we accurately predict changes in affective states over time? Recent theoretical work situates emotions as an active inference process (Barrett, 2017; Smith et al., 2019), positing that emotions emerge through the processing and interpretation of changes in affect (Cunningham et al., 2013). While these models offer proof of principle that affective processes can be formally modeled, to date, there is a lack of empirical evidence supporting these claims. The DAG would be an ideal tool to precisely and mathematically document changes in affect as participants read a thrilling novel or watch a romantic movie. By supplementing theory with data, we can fill in the gaps in our knowledge of how context changes (e.g., scene transitions) or belief inferences (e.g., learning secrets about a character's past) produce and alter affective states (and vice versa). Another open question revolves around how people psychologically represent and structure their affect space and how this representation relates to choice. Asymmetric effects of positive and negative experiences are well documented in other domains (Kahneman & Tversky, 1979; Taylor, 1991), which suggests that a similar effect might be found in the domain of affective representation. For example, a shift in affect that crosses a psychological boundary in affect space (i.e., crossing from unpleasant to pleasant or from low-to-high intensity) may have a stronger influence on the types of choices made compared to a shift in affect of the same magnitude, but within a boundary or quadrant. This idea, which relates to emotion granularity (Barrett, 2004; Demiralp et al., 2012; Feldman, 1995), might explain how affective reference points and individual differences in the representation of affect space bias choice.

The DAG can also be creatively used to capture other elements of the affective experience and to measure its impact on choice. For example, we recently inserted the DAG at multiple different time points within a trial of a social decision-making task, which allowed us to mathematically compute differences between affective expectations and actual affective experiences (Heffner et al., 2021). These differences in affect over the course of a social interaction can be construed as affect prediction errors or violations of expected affective experiences. One strength of using such an approach is that prediction errors in other domains, predominately within the purview of reward, have been extraordinary useful in describing a range of behaviors (King-Casas et al., 2005; Pessiglione et al., 2006). In fact, reward prediction errors serve as the foundation for virtually all standard models of learning and decision-making (Schultz & Dickinson, 2000; Schultz et al., 1997; Sutton & Barto, 2018). Thus, by co-opting the logic of an error-based learning signal, we can test how affect stacks up against reward during learning and decision-making paradigms. Participants were asked to rate their subjective affective experiences (valence and arousal) at two timepoints during the Ultimatum Game: first, at the beginning of the trial before there was any monetary offer from the Proposer, which captures participants' affective expectations, and second, after the Proposer makes an offer, which captures their affective experience. We then mathematically computed the difference between expectations and experience in the granular coordinate space of the DAG separately for the valence and arousal dimensions, to reveal that valence and arousal prediction errors actually outperform (are better predictors of) decisions to punish than reward prediction errors (Heffner et al., 2021).

One major benefit of the DAG is that, because it is agnostic to any one emotion theory, it can operate in a manner that is untethered from any emotion subfield, thereby circumventing many of the ongoing debates. Indeed, almost all (if not all) emotion researchers recognize valence and arousal to be relevant to the experience of emotion, which means that they can easily be used in combination with other methods to broaden our understanding of the human emotional experience. For example, researchers interested in understanding the relationship between self-reported feelings and physiological changes in the body could implement ambulatory at-home electroencephalographic sensors (Eldar et al., 2018) or deploy neuroimaging while subjects make affective ratings on the DAG. This would allow researchers to map self-reported affective states to neurobiological signals to understand whether there is a one-to-one mapping between self-reported measurements and those elicited from the brain and body. Other researchers may want to understand how appraisals or goals change an individual's affective experiences. To capture higher dimensional features of the emotional experience, such as appraisals of safety or control (Cowen & Keltner, 2017; Ortony & Clore, 2015) or goal states (Nelissen et al., 2007), researchers can merge the DAG with other emotion frameworks to assess their interactive effect. In each test case, the DAG does not need to be used in a siloed manner, and its use should not preclude the reliance on other tools or measurements. In fact, by combining multiple measures of emotions, which can each capture different features and levels of the emotional experience, we have the potential to revolutionize our understanding of emotions.

Limitations

While the relevance of valence and arousal to emotion seems undeniable, we readily admit, as others have argued before us, that the world of emotions cannot always be boiled down to a two-dimensional space (Fontaine et al., 2007). The DAG is only capable of capturing a low-dimensional, descriptive map of consciously accessible subjective feelings, which is just one of the many ingredients that comprise a complex emotional experience. For example, without additional metrics, the DAG falls short of being able to distinguish between emotional experiences that occupy similar places in the valence-arousal spectrum (e.g., anger and disgust). Because the DAG also exists in a continuous two-dimensional space, it becomes difficult to parse either dimension into subscales—a method used with other measures (Watson et al., 1988) that allows for the identification of mixed (simultaneous negative and positive valence) emotional states (Trampe et al., 2015). We also acknowledge that there is disagreement about which two-dimensional space best characterizes affect. Some theorists have proposed a 45° rotation of the valence-arousal space that yields dimensions of positive arousal (approach-motivation) and negative arousal (avoidance; Knutson & Greer, 2008). Other theorists have suggested that a three-dimensional space would better capture the human emotional experience (Demekas et al., 2020), including how emotions unfold when people mentally time travel (i.e., simulating the future or remembering the past). In principle, the DAG can be modified to fit any orthogonal dimension (one of its many benefits), and future research should examine which mapping and aesthetic choices (e.g., grids demarking boundaries) are most intuitive for participants.

Conclusion

Although we are not the first to propose that a variant of the affect grid can help researchers better understand emotion—indeed, a version of the affect grid dates back to the late 1800s (Wundt, 1903)—we are proposing that modernizing the affect grid will make it a powerful tool for creating a flexible yet unified framework for examining the role of emotion in decision-making. Especially in the age of big data, it is imperative that decision researchers embrace affective measurements that can provide rich, continuous observations and that can allow for generalization across tasks by serving as a common foundation. Without such a tool, we will continue to lack a deeper understanding of how even low-dimensional affect influence decision-making, which will leave us stumbling in the dark as we search for answers to bigger questions.

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