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THEORETICAL ARTICLE

A Comprehensive Behavioral Model of Emotion Rooted in Relational Frame Theory and Contemporary Extensions

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Abstract

There exists a vast literature on affect and emotion in psychological disciplines, yet contemporary conceptualizations and technologies to predict and influence emotion have been slower to emerge in behavior analysis. The current article is an attempt to conceptualize emotional experiencing through a radical behavioral lens using relational frame theory (RFT) and contemporary extensions. RFT provides a behavioral approach to cognitive appraisal within existing models of human emotion by emphasizing derived relational responding, transformation of stimulus function, and generalized reinforcement learning. Relational density theory (RDT) and the hyperdimensional multilevel (HDML) framework both expand upon RFT and may allow for a more complete account of emotional experiencing within complex networks. Synthesizing these two approaches yields multiple testable predictions that are consistent with RDT across levels of the HDML. Moreover, the ROE-M (relating, orienting, and evoking functions within a motivational context) is a dynamical unit that may be readily evident within emotional experiencing as it is generally described within the psychological literature, and compatible with the synthesized model. Taken together, these approaches and emerging research on affective dynamics may provide a starting point to develop a robust and comprehensive analysis of human emotion that can strengthen behavior analysis and therapies

Keywords Emotion · Relational framing · Relational density · Multilevel framework

I sat with my anger long enough until she told me her name was grief.— C.S. Lewis

In 2022, roughly one in four adults (23.1%; ~59.3 million) in the United States have a diagnosed mental health concern (U.S. Department of Health & Human Services, 2023). Mood disorders are a leading cause of psychiatric hospitalization (Brown, 2001; Minnai et al., 2006) and 4.58% of people (~11.4 million) reported having serious thoughts of suicide, representing an increase of 664,000 people since 2021 (Mental Health America, 2022). Anxiety and depression are also leading causes for individuals seeking mental health services in Westernized countries (Terlizzi & Schiller, 2022), which are expressed as an indicator within disorder categories in the *Diagnostic and Statistical Manual*, Fifth Edition (*DSM-V*; American Psychiatric Association, 2013).

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The combined social cost of medications for anxiety and depression in the United States is an estimated $236 billion in the most recent censure (American Psychiatric Association, 2018). Considerable intellectual capital is also allocated toward supporting those experiencing depression and anxiety: there are approximately 600 peer-reviewed journals worldwide dedicated entirely to these topics. Beyond depression and anxiety, emotional dysfunction (i.e., emotional experiences that inhibit well-being) is expressed in a number of other mental health diagnoses, and although a diagnosis does not itself describe the cause of human suffering (Frances & Widiger, 2012), nomothetic diagnostic categories can describe shared experiences and societies willingness to invest in influencing them.

The role behavior analysts give to emotions or other private events within a causal stream of behavior varies considerably (e.g., Baum, 2011; Marr, 2011); however, it would be difficult to infer that these experiences do not occur (Dougher, 2013). Friman et al. (1998) discussed why behavior analysts should study emotion and offered anxiety as a case example. Likewise, Kanter, Busch et al. (2008a, 2008b) discussed sadness and depression in similar terms as issues of immense social importance that are commonly treated using neuropsychiatric interventions. B. F. Skinner, who is largely credited with the radical behavioral tradition from which the applied and experimental subfields of behavior analysis emerged (Moore, 2005), opened the door for a functional analysis of affect and emotions as private events (Skinner, 1945), suggesting that an all-encompassing science of human behavior would necessarily be capable of predicting and influencing "the private world within the skin" (Skinner, 1974, p. 16). This approach differed from traditional approaches of the time in being less concerned about the topography of emotional responses either internally (physiological responses, reported emotional states) or externally (overt behaviors); rather, a functional analysis of emotion required evaluating the contingencies within which emotions are experienced and verbally reported. Viewed in this way, emotional states such as sadness may be conceptualized as co-occurring behavioral responses occasioned by common antecedents and consequences (Skinner, 1953). Most important, emotions are not themselves causal as was assumed within earlier cognitive approaches that invented internal mentalized states to explain behavior (e.g., Beck & Emery, 1985); rather, emotions may operate as part of a behavior stream that is occasioned by present and historical contextual events (i.e., one's learning history) that can be analyzed as such.

Understanding emotional experiences through a behavioral lens is also necessary to further support and refine approaches to behavior analysis and therapy, such as acceptance and commitment therapy (ACT; Hayes et al., 1999) and other third-wave behavior therapies that are increasingly within the scope of practicing behavior analysts with the proper training, supervision, and mentorship (Tarbox et al., 2020; Dixon et al., 2020; but see also Sandoz et al., 2022; Cihon et al., 2022). This analysis goes beyond merely a means to better understanding overt behaviors of historical interest to behavior analysts, but emotions are important experiences in their own right and represent socially valid targets for behavior change in multiple arenas. Most noteworthy is the emerging subfield of *clinical behavior analysis* (CBA, see Sandoz et al., 2019; Sandoz & Fogle, 2021; Dixon & Paliliunas, 2020), which refers to the use of behavior analysis within interventions for clinical disorders, including mood disorders (da Silva Ferreira et al., 2020; Dougher, 2000; Plumb et al., 2009). The scope of a comprehensive analysis of emotional experiencing goes far beyond this subfield, however, because emotions likely play a role in most human behavior that behavior analysts within multiple subfields (e.g., autism services, organizational behavior management, culturo-behavioral science) are interested in understanding, predicting, and influencing (Folette & Batten, 2000; Enoch & Nicholson, 2020).

Nonetheless, barriers to defining and measuring emotional experiences with common terms exist. As noted by Friman (1998) and later by Kanter, Busch et al. (2008a, 2008b), terms like anxiety, fear, and depression are not precise technical terms and are instead rooted in colloquial language. Because of this, measurement and analysis of emotion is a difficult undertaking and can distract from a functional account emphasizing external contingencies of behavior by focusing on mentalistic explanations of emotion (i.e., when assuming emotions, not external contextual events, *cause* behavior outcomes). A second challenge is that the same physiology appears to underlie multiple emotional states, such as fear and anxiety that differ in terms of the circumstances within which they are occasioned (Dunsmoor et al., 2011; Dymond et al., 2018). For example, fear involves a stimulus event that is immediately *present* and accompanied by a physiological arousal response, whereas anxiety involves an anticipated *future* event that is not yet present. Both of these contingencies may occasion similar physiological responses (e.g., elevated heart rate, skin conductance) and even similar experiential avoidance repertoires (e.g., running away), making a topographical analysis of the behavior alone inadequate in distinguishing between fear and anxiety.

Moreover, emotional experiences and complex human language involving deriving relations are linked processes. Children demonstrate equivalence responding by age 2 (Devany et al., 1986) and basic research has established transfers of arousal function and inductive generalization through equivalence classes (Augustson et al., 2000; Fields & Reeve, 2001). As noted by Dymond et al. (2015), however, many of these basic arrangements are far removed from "real-world" emotional learning, which may be considerably more complex and involve multiple categorization and semantic networks. This claim echoes sentiments by Dixon et al. (2018) that more complete explanations and analysis of behavioral phenomenon are necessary to better serve the world. If we (behavior analysts) are to attempt to predict and even influence emotional experiencing within behavior analysis, it is critical that our *analysis* is sufficiently comprehensive to address the complexities of emotion that are entangled with human language and cognition. Schlinger (2017) stated "to be a behavior analyst means to analyze behavior, and to analyze behavior means to conduct an experimental analysis, also called a functional analysis" (p. 334)—this has the potential to extend to the analysis of emotion as part of a behavioral response within a functional environmental context. Sandoz et al. (2022) made clear the fundamental importance of functional assessment and analysis within ACT-based approaches when developed by behavior analysts, which must be ongoing and explicit, and this reasonably includes an analysis of public and private emotional behavior.

Therefore, the purpose of the present article is to develop a comprehensive account of affect and emotion that extends

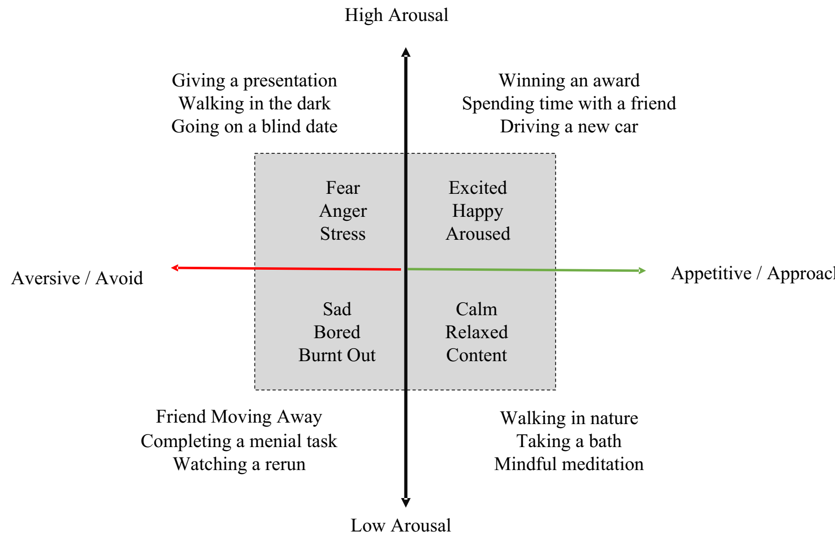


Fig. 1 Diagram Showing the Interaction between Valence (Left to Right) and Arousal (High and Low). *Note*. Affective experiences are described in the inner grey area and contexts that occasion affective experiences are adjacent the experiences

beyond traditional cognitive accounts and can allow for a functional analysis of emotional experiencing. First, we provide a model of emotion based on the general psychological literature as a starting point and extend this model to include functional environmental functions and verbal behavior within radical behaviorism. Second, we summarize how relational frame theory (RFT) introduces derived relational responding and changes in emotional experiencing through transformation of stimulus function. Third, we synthesize two more contemporary extensions of RFT, relational density theory (RDT; Belisle & Dixon, 2020a, 2020b) and the hyperdimensional multilevel (HDML) framework (Barnes-Holmes et al., 2020), which allow for a much more robust analysis of not only relational framing, but emotional experiencing from a radical behavioral lens. Finally, we describe some advances in the emerging study of affective dynamics that can speak to a dynamic interplay between relational responding and emotion that is consistent with both RFT extensions.

Emotion and Affect in the Psychological Literature

Terminological distinctions in the emotion and affective literature can be imprecise, posing a challenge when translating to a functional analytic model. As noted by Ekkekakis (2013), "the theoretical and empirical literature on affect, mood, and emotion is extremely convoluted, reflecting more controversy than consensus" (p. 5). In some contexts, *affect* and *emotion* are used interchangeably, and in others, affect refers to the experiential and behavioral elements of emotion (Kaplan & Sadock, 1991). Gross (1998) adopts the term *affect* as a superordinate term (umbrella term) that encompasses valanced emotional states (e.g., anger, sadness) and episodes (e.g., fighting, hearing bad news), moods (e.g., depression, euphoria), dispositions (e.g., liking, hating), and traits (e.g., cheerful, irascible). Emphasis is placed in some literature on respondent reflexes occasioned by environmental stimuli and the cognitive construction of emotions that allow humans to navigate their social world (Izard, 2007; Barrett & Russell, 1999). Emotions and mood can be distinguished by their contextual sensitivity and temporal extent (Beedie et al., 2005; Fox, 2018), where emotions are shorter in duration and more sensitive to changes in the environment, whereas mood can be longer in duration and less sensitive to changes in the environment. However, as noted by Beedie et al. (2005), commonalities across sources provide only about 60 percent overlap in both the scientific and non-scientific literature when distinguishing between affective experiences making a distinction between the two difficult to operationalize for more objective analysis.

Affect researchers have also distinguished between *arousal* and *valence* functions of emotional stimuli that seems to be more consistent and can inform a general psychological model (e.g., Kuppens et al., 2013). Figure 1 shows how emotional responses and context can be conceptualized along these dimensions. First, the physiological response(s) within emotional experiences can be described as high or low arousal correlating with the activation or suppression of behavior (high arousal describes activation and low arousal describes suppression). Second, valence ranges from positive to negative, where positive affect describes an appetitive experience containing approach functions, and negative affect describes an aversive experience containing avoidance functions. For example, anger may be a high arousal negative affective experience that involves feeling angry and behaviors associated with anger, such as yelling at another person or walking away from a situation. On the other hand, calmness may be a low arousal positive affective experience that involves feeling calm and behavior associated with calmness, such as casually observing one's environment while walking through a forest. Viewing affect in this way may be deeply compatible with existing behavioral paradigms. Low-arousal negative affect can occur in the context of ongoing aversive stimulation (e.g., completing menial tasks), whereas high-arousal emotions like anxiety or fear may occur when an aversive future outcome can be avoided, thus evoking higher rates of behavior. On the other hand, positive affective experiences may operate within both positive and negative reinforcement contingencies. For example, low-arousal states may occur in contexts in which a person is generally "content" and is therefore engaging in less variable behavior to escape or avoid the current context; whereas high arousal emotions like excitement may occur in contexts where high rates of behavior are needed to obtain or maintain positive reinforcers, like competing in sport or preparing to spend time with close friends. This basic assumption that emotion is experienced within an environment is foundational to a radical behavioral approach to emotion that informed the current model.

According Schachter and Singer's (1962) two-factor theory of emotion, emotional experiences contain both physiological and cognitive appraisal elements that appear to interact in dynamical ways within emotional experiences (Ying, 2022). Both processes operate along with overt behavior that is necessary to contact external contingencies for a contextual account (Dixon et al., 2023). For example, a person is walking through the woods, and they see a snake moving through the grass. The initial movement of the grass may elicit a high arousal physiological response (e.g., elevated heart right) and immediately occasion behavior like jumping backwards and screaming. The observing self (or self-as-process from an RFT perspective; Törneke, 2010) perceives both the physiological response and overt reaction, cognitively appraises that the moving object was "a snake in the grass," and the emotion that they experienced was "fear" (for example, through a history of generalized reinforcement by the verbal community, or tacting; Skinner, 1957).

All three responses (physiological reflexes, overt behaviors, and cognitive appraisals) comprise a fear response class that can be understood functionally in multiple ways, including as operating within a three-term contingency that includes attending to the grass and seeing the movement of the snake, the fear response as a complex behavior with multiple elements, and consequences that can serve to strengthen or weaken the response class.[1] For example, negative reinforcement in the form of avoiding the snake or scaring it away may strengthen attending to the grass, the behavior of jumping and screaming, and appraisal of the situation as containing a "dangerous snake" and being "scary." The following sections will attempt a deeper analysis emphasizing the role of verbal behavior and relational framing within what affective psychologists refer to as cognitive appraisal (i.e., cognitive appraisal theory; Omdahl, 2014; Smith & Kirby, 2001). In this general framework, *cognitive appraisal* refers to the sense-making that occurs in response to the experienced event, generally appraising events as pleasant or harmful with respect to well-being or future oriented goals (Omdahl, 2014). Simply describing cognitive appraisal as something people do fails to clarify the functional context within which appraisals that support or fail to support values-consistent behavior change occur. Deeper analyses of emotion, including cognitive appraising, have emerged from the radical behavioral literature and early conceptualizations of RFT than can inform a more behavioral and comprehensive model.

Radical Behaviorism and Emotion

Radical behaviorism extended methodological behavioral approaches to psychology by allowing for a functional analysis of *all* behavior, including private events such as thoughts, perceptions, emotions, and moods (see Moore, 2007). Skinner's (1953, 1974) approach to the topic of emotions may be compatible with and offer greater insight to more general emotion psychological theories described above. Figure 2 combines Schachter and Singer two-factor theory of emotion and a radical behavioral conceptualization. In this model, emotions are considered response classes that include physiological responses, external stimuli, and one's historical interaction with those stimuli (i.e., learning history; Estes & Skinner, 1941). If in the past a stimulus was present, such as a dog, that co-occurred with being bitten by the dog causing a feeling of pain, seeing the dog or other dogs in the future may elicit physiological arousal. The circumstances surrounding dogs are important in the context of emotion. For example, if a dog is immediately present then the physiological arousal may be best described as "fear" that may occasion escape behavior such as running away or staying still to avoid the dog. On the other hand, if the dog were not immediately present but there were events in the environment indicating that the dog may appear, such

[1] Use of the terms *response strength* and *response class* are used consistently with Palmer's description of these constructs (Palmer, 2009, 2021; but see Simon et al., 2020) and are central to modeling relational operants described later in the article. Response strength encompasses response probability but is not restricted to only the behavior that is eventually emitted or observed and broadly applied to multiple behavior dimensions (e.g., rate, latency, duration, magnitude; Palmer, 2009). A response class is the behavioral component of an operant that, once established, can come under control of multiple variables and emerge as fluent and coherent units (Palmer, 2021).

Footnote 1 (continued)

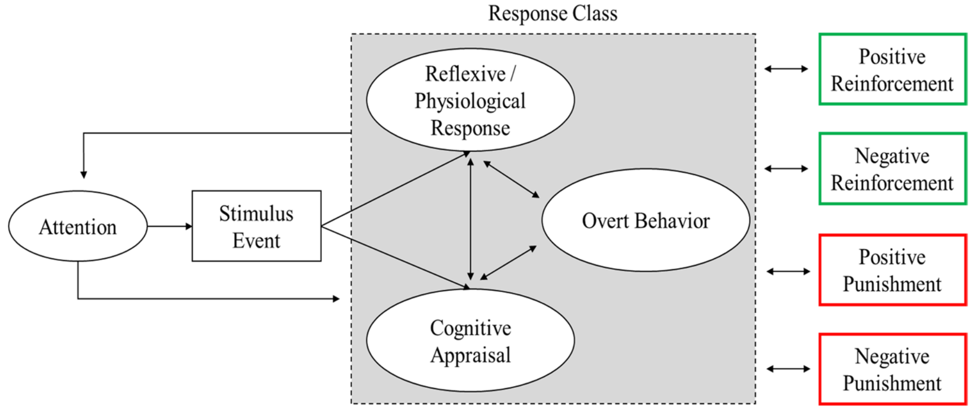


Fig. 2 Diagram Showing the Interaction between Antecedent Behaviors and Context Events; Affective Experiences as a Response Class including Physiological Reflexes, Overt Behaviors, and Appraisal; and Consequences that May Strengthen Elements of the Response Class

as getting into the car to go to visit one's grandparents who own the dog, the same physiological arousal response may occur and would be better described as "anxiety." In both cases, the immediate external events along with the physiological reaction are necessary to label (tact), or cognitively appraising the emotion, and how one appraises the emotion and environment can bidirectionally influence the physiological and overt behavioral response. Thus, the response class involves multiple interacting behaviors that are likely dynamical (i.e., a change in one element influences a change in the other elements, within an evolving stream).

When referring to cognitive appraisal of emotions, Skinner (1945, 1957) provided an account of how people learn to talk about emotions as private events that involve reinforcement learning mediated by a listener who observes and reinforces accurate tacting of emotions in the context of collateral responses, public accompaniment, and metaphors. For example, a child emitting the tact, "I am feeling sad" may occasion reinforcement from the listener when a new toy is broken (public accompaniment) and the child is crying (collateral responses), where "sadness" is abstracted from the contingency of losing access to the intact toy as a reinforcing item and the behavior of crying. On the other hand, if the child was instead laughing and all toys appeared to be intact, then the same utterance "I am feeling sad" may be less likely to be reinforced by the listener, especially when the tact is not yet clearly in the child's repertoire (in colloquial terms, it is unclear if the child knows what the word sad means). Overt behavior is likely necessary in the initial stages of learning to cognitively appraise because without overt tacting of the emotional experience, there is no appraisal that can be reinforced by the verbal community. Metaphors also necessitate observable events to convey emotional experiences. For example, the term "dull pain" operates using the metaphor of a dull (in contrast to sharp) external object and tactile perception of it when contacting the skin. "Butterflies in my stomach" is an expression that conveys nervousness as a fluttering sensation that may be produced by a butterfly's wings but felt internally. The necessity for an external listener, and therefore the overt expression of emotional responding, may lessen as the speaker becomes the listener within the same skin (Skinner, 1974).

Skinner was right to point to the interplay between emotion and verbal processes. Early radical behavioral models described emotion as an on-going adaptive process that is responsive to external circumstances. Ferster (1973) suggested that depression may be maintained by escape or avoidance contingencies within both public and private experiences. Likewise, Lewinsohn (1974) assumed that lean schedules of reinforcement in the environment directly influenced experiences of depression (i.e., depression describes reduced behavior maintained by low levels of reinforcement, as expressed in the matching law). Exposure-based therapies like systematic desensitization and flooding incorporate repeated exposure of emotional stimuli in order to habituate or diminish the physiological arousal responses and overt behaviors typically occasioned by the stimuli. The evidence-base supporting exposure therapies is vast, including in the treatment of posttraumatic stress disorder (Rauch et al., 2012) and phobias (Botella et al., 2017). Behavioral activation emphasizes operant rather than respondent learning processes by increasing contact with positively valanced or reinforcing experiences in the treatment of mood disorders (Kanter, Manos et al., 2008a, 2008b). Several meta-analyses have reviewed interventions that contain behavioral activation supporting its use in the treatment of depression and anxiety (Stein et al., 2021) and posttraumatic stress disorder (Etherton et al., 2021). These approaches emerged from within first-wave behavioral approaches (e.g., contingency management) and are still used to this day in more contemporary second- (e.g., cognitive behavior therapy) and third-wave behavior therapies (e.g., ACT, process-based cognitive behavior therapy; Hayes, 2004; Hoffman & Hayes, 2019).

Where the second- and third-wave approaches differ is in the depth of their analysis of the role of language and cognition within emotional experiencing within an evolving context. The third wave emphasizes the functional role of language and cognition and recognizes the role of reinforcement learning in shaping the language needed to appraise emotional experiences and allowing for generalization of emotional responses across situations (Dymond et al., 2015) and through increasingly complex language networks (Boyle et al., 2016). Given the potentially vast complexity of human language learning that may participate within emotional experiencing, it is unlikely that all (or even most) appraisals have been directly reinforced by a listener (generativity problem) and changes within elements of a multiple response class that includes complex language networks can result in dynamical processes that are not easily understood with more traditional behavior analytic models (complexity problem). RFT provides a contemporary approach to language and cognition that co-evolved with ACT (Hayes, Luoma et al., 2006) that can better account for both the generativity and complexity of emotional experiences from a functional analytic perspective.

Relational Frame Theory and Emotion

RFT expanded on stimulus equivalence theory (Sidman & Tailby, 1982) and is predicated on three core assumptions (Hayes et al., 2001). First, when stimuli share a relationship with other stimuli, those stimuli may come to be related through mutual and combinatorial entailment. For example, a child may learn that a fury animal with four legs that barks is called a "dog" and that "dog" is spelled d-o-g. Without being directly taught, the child may derive that d-o-g refers to a physical dog and that the physical dog can be described to others using the symbols d-o-g (i.e., combinatorial entailment). Relations go beyond simple coordination, or can be responded to relationally in different contexts (C-rel). "Dog" is contained in the hierarchical category "animal" along with "cat" and "zebra," where "dogs and cats" are common house pets and "zebras" are not (C-rel = hierarchy, animals-pets). "Dogs" are bigger than "tennis balls," are smaller than "buildings," and "grandmother owns one" (C-rel = comparison, size). Second, when entailed relations exist, the function of stimuli in the environment may be transformed by the entailed relation (i.e., contextual function, or C-func). To continue with the above example, if a person is bitten by a dog, hearing the word "dog" or reading the text d-o-g may also occasion fear, which includes the entire response class described above (physiological changes, cognitive appraisal, overt behavior change; C-func, dog = fear). On the other hand, a positively valanced history such as cuddling with dogs may result in positive emotions when talking about or reading about dogs (C-func, dog = happy). Finally, all of this occurs as a generalized operant, where the ways in which people relational respond and the act of relating itself is shaped through reinforcement of multiple exemplars of derived relational responding (see Barnes-Holmes & Barnes-Holmes, 2000; Healy et al., 2013).

In the context of affective experiences like emotion and mood, the way people feel and react (as a response class) occurs because feeling and reacting in this way under similar circumstances has historically contacted reinforcement and avoided punishment. This extends to cognitive appraisal that involves relational framing and potentially vastly complex relational networks. In the case of behavior therapies, we may be more interested in overall probability of emotional response classes and the organization (or, self-organization) of large networks than any specific content or relata within a given network. For example, whether or not a person experiences positive or negatively valanced emotions in response to dog networks is less important than if a person experiences positive or negatively valanced emotions in general, and potentially under ambiguous circumstances where events could be appraised in multiple different ways.

Blackledge (2003) provided an RFT account of Lang's (1985) fear network that provided a "popular and widely-known cognitive model" (p. 421) of fear. They provided the example of cognitively appraising the presence of a snake in a wooded area that is similar to our example above. Figure 3 adapts this network in the ambiguous context of taking a college examination that may occasion either fear or excitement in graduate students. In the fear network, the context of the examination occasions verbal relations of flunking the course that leads to failing to graduate and perception of self as both a bad student and a failure. These relations are negatively valanced and increase the potentially negative reinforcing value of avoiding contextual events surrounding exam taking (e.g., preparing for the exam, taking classes that contain challenging exams) that strengthen (i.e., make more probable) avoidance behaviors like procrastinating or adopting an easier path to graduation. For another student (or the same student in another context), the same examination may occasion verbal relations of passing the course and graduating from the program that support perception of self as a good student and a success. Likewise, these positively valanced relations may increase the positive reinforcing value of taking the examination, strengthening behavior such as preparing for the examination and electing to take more challenging coursework when doing so aligns with valued outcomes.

An RFT interpretation of emotion is predicated on the assumption that language does not only involve tacting of private events, but that verbal relations also influence other elements of emotional experience like physiological arousal and overt behavior (i.e., the relationship is bidirectional) through the transformation of stimulus function. This relationship is well evidenced. For example, transfers of aversive function have been established through shock (Augustson & Dougher, 1997), affective images (Lang et al., 2005), and

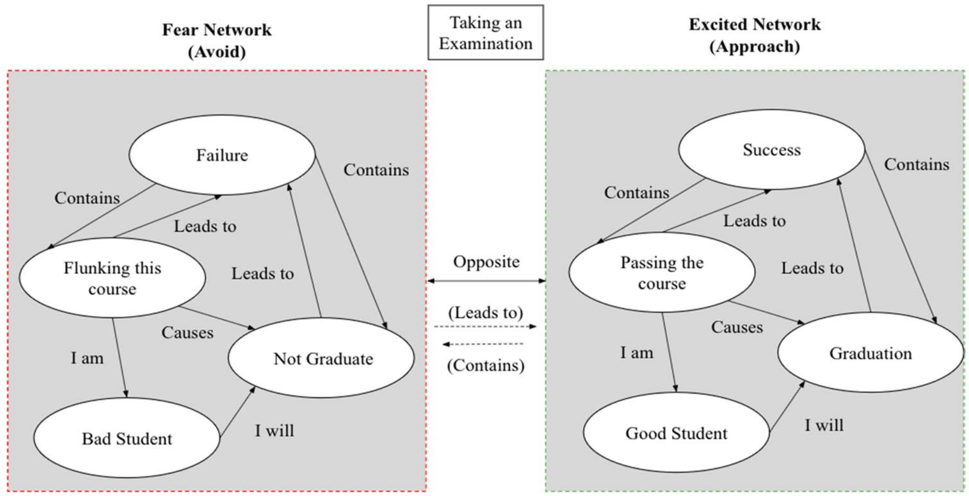


Fig. 3 Diagram Showing Relational Networks that are Positively Valanced (Approach) and Negatively Valanced (Avoid) Based on Blackledge's (2003) RFT Reinterpretation of Lang's (1985) Fear Network as a Model of Cognitive Appraisal

aversive sounds (Dymond et al., 2007). In a general arrangement, the aversive stimulus is correlated with an unfamiliar image to establish a respondent function, then coordinated relations are established such that novel unfamiliar images are combinatorially entailed with the initial image and occasion the same physiological response, such as elevated skin conductance or heart rate. Transformation consistent with relational cues beyond coordination have also been established, including opposition (Dymond et al., 2007) and hierarchy (Gi et al., 2012). Appetitive transformations of function have also been demonstrated in the derived and generalized alteration of preferred pictograms (Valdivia-Salas et al., 2013) and within sexual arousal functions (Roche et al., 2000). The relationship between relational framing and overt behaviors is also well documented in translational studies, such as in gambling when positive and negatively valanced stimuli are paired with different colored slot machines that influence gambling behavior (Zlomke & Dixon, 2006), or more recently in the context of purchasing related to climate change (Matthews et al., 2022).

Incorporating an analysis of relational framing within cognitive appraisal can strengthen a functional analytic account. When viewing Figure 3 from an ACT approach, the relationship between the positive and negative networks is not only that of opposition, but when responding flexibly in the service of chosen values, aversive experiences may lead to appetitive experiences augmented by behavior repertoires built through therapy (e.g., the six core processes of the ACT Hexaflex). In this way, appetitive experiences also contain aversive experience, emphasized within acceptance of *all* experiences—both positive and negative. The evidence-base supporting ACT as a general approach, and psychological flexibility as a behavior change process, is substantial (Hayes, 2022; Hayes et al., 2022); however, as noted by McLoughlin & Roche (2022) more well-controlled research is needed and the link between RFT and ACT is not explicit. This sentiment was also echoed by Assaz et al. (2022) when offering a more detailed RFT conceptualization of cognitive defusion within the ACT Hexaflex model. Further, Belisle and Dixon (2022) suggest that describing the relationship between RFT and ACT (and likely other therapy approaches) "may require approaching relational behavior as dynamic and self-organizing instead of as a static configuration of specific 'relational frames' at any singular moment" (p. 71). Therefore, achieving a more complete understanding of the relationship among RFT, emotion and affect, and third-wave therapies like ACT may require a deeper analysis of relational behavior to more fully account for cognitive appraisal underlying emotional experience in a way that is consistent with behavioral processes (whereas cognitive appraisal without further analysis is more consistent with a cognitive psychology tradition; see Harte et al., 2023).

Extending RFT: Relational Density Theory and the Hyperdimensional Multilevel Framework

The potential complexity of relational symbolic networks is vast and not easily accounted for in small network studies with three or four network members that are often evaluated in laboratory arrangements (Dymond et al., 2015; Belisle, 2020). Boyle et al. (2016), for example, utilized a semantic generalization paradigm (Eisen, 1954) to evaluate how fear responses generalized through a complex semantic network. In their study, a word (e.g., broth) was paired with the presentation of shock to elicit a fear response while an unrelated word (e.g., assist) operated as a control. Participants could then engage in an avoidance response in the presence of the conditioned word to cancel the presentation of the shock. In a test phase, words semantically related to the conditioned word were presented, and their results showed that both avoidance responding and skin conductance were elevated given the presentation of semantically related words. Given the number of potentially related words or events to any familiar or meaningful verbal stimulus, real-world transformation of affective functions may be considerable. Thus, translating RFT to direct clinical applications necessitates expanding the initial RFT framework laid out by Hayes and colleagues nearly 30 years prior to the writing of this article (Barnes, 1994; Hayes et al., 1996).

Two contemporary conceptual developments may provide a starting point for the development of a more expanded functional model, including relational density theory (RDT; Belisle & Dixon, 2020a) and the hyperdimensional multilevel (Barnes-Holmes et al., 2020) framework. In this section, we describe both of these RFT extensions in terms of emotional experiencing. It is important to note that RDT is a theoretical extension of RFT that makes explicit predictions about relational responding by synthesizing RFT and behavior momentum theory (Nevin & Shahan, 2011; Belisle & Dixon, 2020a). Recent research on RDT has utilized the multidimensional scaling procedure (MDS) as an analytic strategy to analyze complex relational networks (it is also important to note that MDS is not the only, nor necessarily the best way, to evaluate relational properties within RDT; see Clayton & Hayes, 2004, for first application of MDS to evaluate relational framing). The HDML is a framework for describing and categorizing relational behavior across multiple levels and dimensions that can expand the depth and scope of RFT and, consequentially, RDT. Both RDT and the HDML assume that differences in relational response strength are important for capturing relational behavior in flight. In the case of the HDML, this assumption informed the development of the implicit relational assessment procedure (IRAP; Barnes-Holmes et al., 2006) as an analytic strategy (Barnes-Holmes et al., 2020).

In linking both RDT and the HDML, we assume that differences in relational response strength are important for capturing relational behavior in flight. Moreover, both RDT and the HDML assume that relational behavior operates from within a relational field, such that all elements of a relational system are interconnected and therefore changes to the relational system are likely dynamical. *Dynamical*, used here, refers to a change in one element of a multielement system resulting in changes in other elements (Belisle & Dixon, 2022), where a change at T time can result in a corresponding change at T+1, and the change at T+1 can result in a corresponding change at T+2. Therefore, RDT and the HDML are compatible and contemporary advances that both build on RFT in different ways. RDT offers a theoretical extension of RFT by introducing higher-order concepts whereas the HDML provides a systematic framework from which is interpret relational responding.

Relational Density Theory

RDT synthesizes assumptions and prior research on RFT with principles described within behavior momentum theory (Nevin & Shahan, 2011) to account for dynamical interactions within relational framing occurring within a functional environmental context (Belisle & Dixon, 2020a). Within RDT, these interactions occur both within and between relational classes and are expressed quantitatively (Belisle & Clayton, 2021). Quantitative analysis is made possible by considering C-rel and C-func as continuous functional properties that operate along a continuum of response strength, rather than as dichotomous relational events, that is largely consistent with RFT from its inception (i.e., C-rel and C-func are interdependent, if not equivalent, phenomenon). Thus, RDT assumes that nonlinearity may be observed and predicted given knowledge of differential relatedness (or degree of relatedness; Fields, 2016) within relational networks. For example, a dog, a cat, and a fish are all related under the category "animal," but differ in that cat and dog are more related than are dog and fish or cat and fish. Dogs and cats are connected through multiple relations within dense networks. Both are common household pets, have fur, are land-based, have four legs, are mammals, may cuddle with you, necessitate veterinary care, and the culmination of these lower-level relations supports the relational strength of dog–cat more so than dog–fish and cat–fish. If a person has never interacted with a dog, then they may respond to the dog in terms of the cat response repertoire, and if a person has never interacted with a cat, then they may respond to the cat in terms of the dog response repertoire. On the other hand, the same person is less likely to respond to the fish in terms of either the cat or dog repertoire. This relationship is considered nonlinear because although the hierarchical relationship is the same between all three animals, the response output is not (i.e., the animals are differentially related that can be used to make predictions about relational responding).

The initial conceptual article on RDT (Belisle & Dixon, 2020a) summarized potential sources of nonlinearity within coordinated relational networks and reviewed relevant research showing these effects. Borrowing from behavior momentum theory and Newtonian classical mechanics, a first equation was proposed for the concept of relational resistance as:

$$\Delta R = \frac{-x}{Rm} \tag{1}$$

Where ΔR describes a change in relational behavior that is predicted by $-x$, or a counterforce applied against the relational behavior (e.g., counterconditioning), and Rm, or relational mass as an estimate of resistance to change. Thus, relational responding that operates at higher mass is more resistant to incompatible changes in the environment. Two properties of relational networks appeared to predict relational resistance in the existing literature and were compatible with extending the equation to:

$$Rm = R\rho * Rv \tag{2}$$

Where $R\rho$ describes the relational density of the network, or the strength of entailed relations within the network, and Rv describes the relational volume of the network, or the number of relations or nodes contained within the network. Whether Rv best described class size (total number of members) or nodes (total number of combinatorially entailed relations) was left ambiguous given ambiguities in the existing literature at that time, but a recent study conducted by Cotter and Stewart (2023) suggested that Rv may yield stronger predictive utility when referring to nodal distance rather than class size. It is important to note that class sizes and nodal distance covary in many but not all instances, where a larger class is likely to contain more nodes than a smaller class. For example, a six-member class can contain one to five nodes, but a four-member class can only contain one to three nodes.

In regard to $R\rho$ when Rv is held constant, Belisle and Dixon (2020b) explored this directly by comparing changes in responding in equivalence classes when one relation in a network was counterconditioned. The relational density of the classes, expressed as percent accuracy and response latency, was predictive of the resistance of the class to change when holding the size of the class constant (size did not seem to influence the outcome, consistent with results reported more recently by Cotter & Stewart [2023]). This outcome mirrors data on the use of meaningful stimuli within equivalence classes, where the inclusion of stimuli that are more meaningful (i.e., participate in higher mass networks preexperimentally) may be more resistant to counterconditioning and maintain over time (Bortoloti & de Rose, 2011). Incorporating RDT and the concept of meaningfulness may therefore allow for predicting affective transfers of stimulus function. For example, Bortoloti et al. (2013) demonstrated that overtraining increases the strength of equivalence relations and leads to a graduated transfer of affective functions when one stimulus member is a happy face and the other is an angry face, as measured using a semantic differential scale (Osgood et al., 1957). Overtraining, either experimentally or naturally occurring through differential reinforcement in the environment, among other contextual parameters (Arntzen et al., 2020; Fields & Arntzen, 2018) may serve to increase relational density and promote transfers of affective function. In clinically terms, this would imply that relational frames that are more practiced, contain familiar elements and include emotionally charged experiences, may not only produce heightened emotional responses but may also be highly resistant to change.

Beyond predicting relational resistance, RDT proposes that high-mass relational classes may be more likely to merge when they are more coherent, where *coherence* is defined as the preexperimental similarity between relational classes. Belisle and Clayton (2021) summarized this interaction as:

$$RF = \frac{Rm1 * Rm2}{Rd} \tag{3}$$

In this equation, RF represents a force or attractor between two relational classes ($Rm1$ and $Rm2$), or the probability of a relational response consistent with the class merger, and Rd is the preexperimental difference or distance between the classes. In a physics gravity metaphor, force or attraction describe nonlinearity in movement toward a mass. For example, an object near earth's atmosphere is more likely to move and accelerate towards earth's surface than any other direction in space. In the context of relational responding, the merging of relational classes is more likely when $Rm1$ and $Rm2$ are both high (contain multiple strong relations) and Rd is low. In the study conducted by Belisle and Clayton (2021), four 4-member classes were established that each included a familiar word (salt, pepper, king, queen) and three unfamiliar symbols. Participants were then randomly assigned to a coherence group and a noncoherence group in a class merger phase. The coherence group received points for matching a member of the salt class with a member of the pepper class, and a member of the king class with a member of the queen class; these pairs were reversed for the noncoherence group. Results showed a clear formation of separate merged classes in the geometric space for the coherence group (king–queen, salt–pepper), whereas no separation was observed for the noncoherence group in this arrangement (king–salt, queen–pepper).

Figure 4 expands on the fear and excited relational network shown in Figure 3 by demonstrating how relational density and volume may interact within complex networks, specifically organizing around affective dimensions. As noted by Kahneman (2011), experience, including remembering and evaluating, may organize around affective experience as a dynamical process that develops over time. In the figure, high density networks have less space between stimuli and high-volume networks contain a greater number of stimuli. On the left, greater density and volume are observed in the negative affective network in the context of taking an examination, where the C-func includes the examination context and the emotional experiencing of the examination context. For the student whose responding is shown in the left of the figure, ambiguous stimulus events are likely to transfer to an examination context and may be more likely to occasion negatively valanced emotional

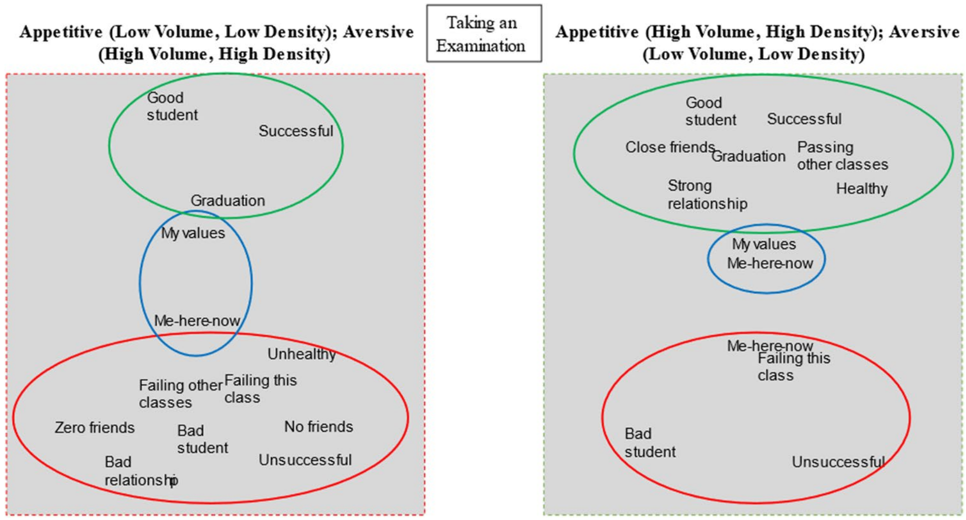


Fig. 4 Diagram Showing Relational Networks that are Organized along the Dimension of Positive (Top) and Negative (Bottom) Affect. *Note*. Adapted from Belisle and Dixon's (2020a, 2020b) model of relational volume and density

experiences. Moreover, the deictic stimulus "me–here–now" in the context of taking an examination may be closer to the negative affect network and farther from identified values (positively valanced stimuli, see Paliliunas et al., 2024) of being a good student, graduating, and achieving success as a student. For the student whose responding is summarized on the right, greater density and volume are observed in the positive affect network, suggesting that this student may interpret ambiguous stimulus events in the same examination context more positively. In addition, a stronger relation (and therefore likely part of a denser network) between "me–here–now" and "my values" is apparent that may be expected when responding is psychologically flexible (i.e., behavior and experience is aligned with chosen values; Paliliunas et al., 2024; Dixon et al., 2023).

Results like those shown in the hypothetical case of college students taking an examination were reported by Paliliunas et al. (2024). In a first study, college students completed the Personalized Psychological Flexibility Index (PPFI; Kashdan et al., 2020) and an MDS measure that included positive and negative affect terms from the Positive and Negative Affect Scale (PANAS; Watson et al., 1988), personalized stimuli related to values, strengths, challenges, and thoughts and emotions, as well as the deictic stimulus "me–here–now." Results in the MDS showed that participants who scored high in psychological flexibility on the PPFI also showed closer proximity of me–here–now to values, strengths, and positive affective stimuli; whereas participants who scored low in psychological flexibility showed closer proximity of me–here–now to the negative affective network, thoughts and emotions, and personal challenges. In a follow-up case study with a college student participant receiving support using Values-Based Self-Management Intervention framework, results showed responding consistent with a low psychological flexibility profile before the intervention and improved psychological flexibility after the intervention using the MDS analysis, that cohered with academic behavior change, suggesting an improvement in both overt behavior and affective experiencing of the university context for this student.

Some early translational studies extending from RDT have also shown that relational stimuli may organize around positive and negative valanced functions utilizing the multidimensional scaling procedure. Results in these studies resemble those in Figure 4. Sickman et al. (2023) evaluated gender pronouns and common attributes associated with masculinity and femininity. When graphed in the geometric space in three separate conditions, their results showed that relations clustered both in terms of gender (e.g., feminine = emotional = affectionate; masculine = aggressive = handsome) and the valence of the term (e.g., neutral, masculine = feminine; positive, affectionate = handsome; negative, emotional = aggressive). Similar findings were established by Belisle et al. (2023) evaluating racial relational networks, where race was one dimension and affect valence appeared to function as the other dimension (i.e., relations clustered into clear networks around positive/negative valence stimuli and black and white images). Finally, Hutchison et al. (2023) evaluated valanced dimensions of climate-change stimuli, where one groups of participants underwent relational training to establish coherently valanced relational networks (e.g., symbol 1 = lush forest, healthy polar bear; symbol 2 = baren forest, unhealthy polar bear), whereas the other group underwent relational training to establish incoherently valanced relational networks (e.g., symbol 1 = lush forest, unhealthy polar bear; symbol 2 = baren forest, healthy polar bear). Results showed greater relational density in the coherence group compared to the incoherence group, and these results corresponded with the changes in consumer purchasing reported by Matthews et al. (2022)

following relational training. Even more broadly, these outcomes in the translational research are supported conceptually by the vast research on emotional properties of stimuli and the enhanced formation of associative networks and memory expressed in the cognitive and affective literature (e.g., Madan et al., 2019).

A limitation of this research to-date is a conceptualization based on equivalence (coordinated) relations. This is due to an inductive approach to exploring RDT by starting with a singular frame and expanding the complexity of the theory based on emerging data and discourse. For example, a common question in the MDS is "how strongly related are these two stimuli?" along with a rating scale ranging from 1 to 10. Different types of relations, or C-rels, may be operating simultaneously controlling the response, where coordination is the strongest relation. For example, in the context of relating two cheetahs, one horse, and one turtle, the cheetahs may be the most proximally related because they are coordinated, whereas the horse may be closer to the cheetahs than the turtle because the horse is bigger, faster, a furrier than the turtle, and both the horse and the cheetahs are mammals. Another limitation is that although the translational studies have contained up to 30 members within a relational network (Belisle et al., 2023), the complexity of relational classes have been more limited in the basic research, ranging from 3 and 6 (Belisle & Dixon, 2020b) to 12 (Belisle & Clayton, 2021) class members. The HDML developed by Barnes-Holmes et al. (2020) provides a conceptual framework that can expand the scope and depth of RDT considerably within a synthetic model, with implications for an analysis of emotions.

Hyperdimensional Multilevel Framework

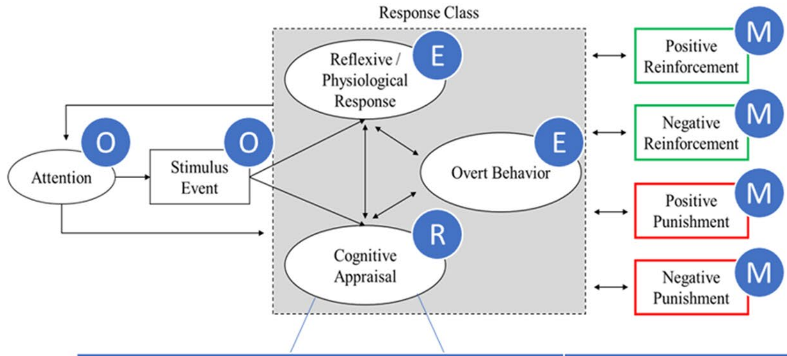
The HDML provides an integrative framework that builds from the multidimensional multilevel framework and the observation of DAARRE effects within the IRAP. The MDML provided a framework for describing research and analytic units within derived relational responding but was limited in its description of the transformation of stimulus function within this framework. The inclusion of the ROE-M (relating, orienting, and evoking functions within a motivational context) provided a conceptual behavior unit that explained DAARRE effects and centered the transformation of stimulus function within the *hyper*-dimensional multilevel framework. With regard to relational framing, the HDML describes 20 units of experimental analysis that are highly interdependent and are metaphorically analogous to geometric fractals in which patterns at lower levels can be abstracted at higher levels, and vice versa (see Belisle, 2020, for a discussion of model dependency and fractal logic). The levels in the HDML include mutual entailing, relational framing, relational networking, relating relations (e.g., analogy), and relating relational networks (e.g., metaphor and stories). The dimensions describe behavior patterns that may occur within each of the levels, and include complexity, derivation, coherence, and flexibility. Within this framework, *complexity* occurs on a continuum where stimuli can be related in many different ways, across relational frame families, with varying degrees of combinatorial entailment, and within relational networks composed of multiple relational frames (Barnes-Holmes et al., 2017). For example, a relational network containing multiple interacting frames of coordination, distinction, and opposition is more complex than a relational frame containing a small number of coordinated relations (range: low complexity to high complexity). *Derivation* refers to how well-practice a relational response is. For example, the first instance of a derived response is higher in derivation than subsequent instances that have contacted reinforcement either privately or publicly (range: low derivation to high derivation). *Flexibility* refers to a change in relational responding in response to context. For example, if two relational responses are observed during a contingency shift, the response that changes the most is the most flexible (range: low flexibility to high flexibility). Finally, *coherence* refers to how patterns of relational responding overlap with previous patterns of relational responding. For example, a relational metaphor that groups objects based on their function may be coherent with a relational network that groups people based on their role in a company (range: low coherence to high coherence).

In synthesizing RDT within the HDML, RDT equations may be predictive at each level of the HDML consistent with the fractal logic of the framework. If a stimulus with a positive affective function is strongly entailed with an unfamiliar stimulus, then the unfamiliar stimulus may be likely to occasion positive affective responding (level: mutual entailment or relational response). Likewise, if a relational network is positively valanced and is strongly related to an unfamiliar situation through the delivery of a metaphor, such as in the context of behavior therapy, then stimuli within the unfamiliar network may be likely to also occasion positive affective responding (level: relating relational networks). The transformation of stimulus function may be predicted by the relational density of the entailed relations within and between relational networks. Moreover, RDT would predict that relational frames, relational networks, relations between relations, and relations between relational networks, are more resistant to change at each level when there is greater nodal distance and relational density within small and large singular or merged networks. Indeed, what precisely constitutes a relational frame, network, or network of networks is fuzzy when all stimuli likely participate in an interdependent relational field where everything is related to everything else, differing only in their relational distance, contextual relations, and contextual functions. Thus, RDT may be critically important at this point in time for interpreting behavioral effects through the lens of the HDML as a complex relational field.

There are terminological differences between RDT and the HDML that should be reconciled to achieve a synthetic model to apply to emotional experiencing. Our attempt here should not be viewed as a final attempt, but rather a first attempt at consolidating language and elucidating important distinctions in the use of technical terms. First, relational density ($R\rho$) and the concept of derivation are likely closely related concepts. The initial instance of a derived relational response is likely the weakest, and so relational responding that is high in derivation is likely to be low in relational density. It is important to note that derivation or practice effects are not the only contextual factor that has been shown to influence relational density as a response property. For example, overtraining of the directly trained response can strengthen the derived response and the inclusion of familiar stimuli within a relational frame can strengthen the relational frame (Belisle & Dixon, 2020a). The latter may be explained by the coherence equation in RDT because familiar stimuli are only familiar in that they operate within higher-mass networks than unfamiliar stimuli, and therefore are more likely to entail new relations in a training arrangement (Belisle & Dixon, 2020b). Second, relational volume (Rv) may be closely related to both the concept of levels and complexity in the HDML. Higher levels in the HDML necessarily contain more relations, including combinatorially entailed relations, as higher levels contain the relations observed at lower levels. For example, relational network contains multiple mutually entailed relations, and a story contains multiple relational networks (and in consequence, even more mutually entailed relations). Thus, Rv will positively covary with increasing levels. Moreover, complex relational systems contain potentially more combinatorially entailed relations and introduce the potential for unknown elements within relational networks (see Smith & Hayes, 2022). For example, if A is different from both B and C, the relationship between B and C is unknown (i.e., ambiguous). We may therefore predict that relational networks with more unknown elements (high Rv) also show lower $R\rho$, consistent with a derivative of Equation 2 expressed in Belisle and Dixon (2020a) and Cotter and Stewart (2023).

Flexibility and coherence in the HDML are most closely related to the higher-order nonlinear properties of resistance and coherence expressed in RDT (Belisle & Dixon, 2020a), but there are important considerations. Flexibility as described in the HDML appears to be identical to the resistance Equation 1, whereby flexibility is inferred based on behavior change observed given a shift in environmental conditions. Thus, resistance in RDT may provide a quantitative and testable prediction of the flexibility of relational responding at multiple levels of the HDML. At the same time, the term flexibility as used in the HDML may differ from the way the term is used in the more common psychological flexibility literature that includes changing *or persisting* in behavior, consistent with valued reinforcing outcomes (i.e., the term flexibility may not be coherent with terms used in behavior therapies that attempt to influence emotional experiencing). This definition of flexibility also more accurately depicts the "bend but do not break" analogy of flexibility. For example, a broken appendage or torn ligament may be easily displaced but is not likely to be considered flexible in the colloquial use of the term. In our opinion, resistance to change may be the more precise term if indeed these concepts are equivalent and is compatible with the behavior momentum theory conceptualization of behavioral resistance. Coherence described in RDT literalizes the overlap between relational networks as the preexperimental distance between networks and predicts the merging of coherent relational networks. However, the concept of coherence within the HDML offers greater scope, and can include not only preexperimental relatedness, but also coherence in types of relations and structures of relational networks. This is undoubtedly useful when moving to an analysis of more complex relational systems and therefore broadens an RDT conceptualization of coherence. Given the fractal logic of a synthesized account, the RDT conceptualization may still be valid. For example, a network with the relational structure A' may be more strongly related to another network with the relational structure A' than a network with the relational structure B', when the differences between stimuli within the networks are held constant. In this case, network structure containing difference C-rels and C-funcs would operate as a higher-level source of relational coherence within a synthesized RDT-HDML model. Much of this is purely theoretical at the time of writing the current article, and this work must progress inductively; however, the current conceptualization is offered to illustrate the potential scope and depth offered by synthesizing these approaches to relational complexity.

We can see this interplay be overlaying the ROE-M with our radical behavioral model of emotional experiencing in Figure 5. In the figure, orienting (O) functions are observed when an environmental event (stimulus) occasions the emotion response class. Any given event contains multiple stimuli differing in their nonarbitrary and arbitrary salience at a given point in time, and events preceding the emotional experience of interest may influence what aspect of the emotion are observed. For example, food deprivation may produce a motivational context (M) where orienting behaviors toward indicators of food availability are more likely to occur. In this case, a stimulus indicating the nonavailability of food may produce an emotional response colloquially described as disappointment or anger. Deprivation also alters the reinforcing value of food, and



	Relational Properties			Higher-Order / Nonlinear Properties	
Levels	Relational Density / Derivation	Relational Volume / Nodal Distance	Relational Mass ($R\rho * Rv$)	Relational Mass / Resistance / Flexibility	Relational Mass / Coherence
Mutual Entailment	$R\rho_{ME}$	-	$R\rho_{ME}$	$\Delta R_{ME} = \frac{-x}{R\rho_{ME}}$	-
Relational Frames	$R\rho_{RF}$	Rv_{RF}	Rm_{RF}	$\Delta R_{RF} = \frac{-x}{Rm_{Rf}}$	-
Relational Networks	$R\rho_{RN}$	Rv_{RN}	Rm_{RN}	$\Delta R_{RF} = \frac{-x}{Rm_{Rf}}$	-
Relating Relations	$R\rho_{RR}$	Rv_{RR}	Rm_{RR}	$\Delta R_{RR} = \frac{-x}{Rm_{RR}}$	$RF_{RR} = \frac{R\rho_{ME1} * R\rho_{ME2}}{Rd}$
Relating Relational Networks	$R\rho_{RRN}$	Rv_{RRN}	Rm_{RRN}	$\Delta R_{RRN} = \frac{-x}{Rm_{RRN}}$	$RF_{RRN} = \frac{R\rho_{RN1} * R\rho_{RN2}}{Rd}$

Fig. 5 Diagram Showing the General Model of Affective Experiencing with the ROE-M Operating within the Behavioral Stream, and Relational Behavior Summarized across Levels and Dimensions of a Synthesized RDT-HDML Model. *Note*. ME = mutual entailment; RF = relational frame; RN = relational networks; RR = relating relations; RRN = relating relational networks

therefore potentially strengthening the effect that locating food can have on both relating within the entire emotional response class. Moreover, motivative augmental functions may strengthen or weaken the reinforcing or punishing effect of consequential events within the behavior–environmental stream. Within the response class, physiological responses and overt behaviors are evoked (E) by the stimulus event. In the current example, the indicator for food nonavailability elicits an increase in heart rate and skin conductance consistent with a high arousal state, and avoidance of the stimulus by approaching different environmental events that are more likely to contain indicators of food availability.

This all occurs in the context of relational responding (R) that operates at multiple levels and dimensions and may be predicted given knowledge of relational volumetric–mass–density described in RDT. In the example, a relational history that establishes several strong relations supporting that food is likely to be found in Location A over Location B is likely to result in an increased probability of searching for food in Location A that may be highly resistant to change (ignoring a friend who says that the food is better in Location B), and show coherence effects like going to Location C when Location A is closed because Location C is more similar to Location A than Location B. The dynamical interaction of the consequated outcomes cannot be overstated. For example, if Location C has food that fails to resemble Location A, this may weaken the relational coherence (increase *Rd*) between these networks, perhaps strengthen the appetitive relations within Location A because the quality of that type of food is rarer, and perhaps even increase the appetitive functions of Location B. Barnes-Holmes and Harte (2022) speak to the potentially dynamical and at times counterintuitive interactions of ROE-M elements when any element of the unit is manipulated, and this is no less true within a synthesized model.

Given the dynamical nature of complex relational response repertoires, emerging research on affective dynamics summarized by Belisle and Dixon (2022) in terms of relational framing could allow for an even more comprehensive analysis. In particular, the research on dynamics within affective systems can provide insight into the dynamic interplay between relational behavior and affective experiencing (that contains relational behavior, R, as part of the interdependent behavior unit, including orienting, O, and evoking, E, functions).

Affective Dynamics

As noted by Trull et al. (2015), optimal health and performance are not a simple function of increasing exposure to positively valanced events and decreasing exposure to negatively valanced events, as emotions ebb and flow over time and in response to internal and external events. Treating emotion as a behavior opens the door for behavior analysts to evaluate patterns within affective experiences and to establish contextual influences. Ecological momentary assessment involves participants reporting behavior in real-time using applications that can be downloaded onto a device, where affective responding can be captured at regular intervals or in response to context events. Trull et al. (2015) linked dynamic patterns in affective responding in psychopathology by distinguishing between affective instability, emotional inertia, and emotional differentiation. Affective instability describes variation and temporal dependency of affect, where high variation and low temporal dependency represents instability. Instability in affective responding is more common in clients diagnosed with borderline personality disorder when compared to clients with depressive disorders who show heightened temporal dependency and lower variability. Emotional inertia describes temporal dependency over time, where clients with major depressive disorders demonstrate strong negative inertia of negatively valanced emotional experiences (Kuppens et al., 2012), that coupled with high stability, can be highly resistant to change in response to therapy or medication. Moreover, strong negative inertia in adolescent depressive patients is predictive of trait neuroticism and low self-esteem (Suls et al., 1998; Kuppens et al., 2010). Finally, emotional differentiation is the ability to discriminate between affective experiences that include arousal functions and situational contexts, which is highly consistent with both the radical behavioral and functional contextual accounts of emotion.

It is important to note that these behavior patterns are not causal of the diagnostic label or vice versa, rather these are consistent behavior patterns that are given nomothetical labels under these diagnostic categories. There may be some evidence that these patterns could inform ACT-based interventions, especially when informed by a more comprehensive account of emotional experiencing like that described here. Houben et al. (2015) conducted a meta-analysis exploring dynamic patterns of emotions including variability, instability, and inertia, showing that highly variable and insatiable patterns with negative inertia correlated with low psychological flexibility, although the opposite patterns were not predictive of high psychological flexibility. Barnes-Holmes et al. (2018a, 2018b) utilized the HDML framework within two clinical case conceptualization to inform ACT-based interventions using a verbal functional analysis to obtain information of relational repertoires maintaining psychological suffering. Using techniques like drill-down that is designed to promote relational coherence involving deictic self-ing networks, the researchers were able to demonstrate positive therapeutic changes in these complex clinical cases, detailing the potential utility of more advanced functional analytic frameworks. Well-controlled comparative research is needed to establish that approaching ACT-based interventions, or any behavior therapeutic intervention through this framework produces more positive outcomes than interventions not informed by these models. Nonetheless, an analysis of this sort may be necessary to ensure that assessment and interventions are behavior analytic and conceptually systematic with established behavior change principles.

With regard to affective dynamics, it is possible that the dynamics observed within emotional experiences mirror relational behavior as they are evoked through the transformation of stimulus function (Belisle & Dixon, 2020a, 2020b). Instability in emotional experiences may predict low resistance (*Rm*, Equation 1) to change, where relational framing patterns are highly sensitive to changes in the environment. A dinner party with family may be progressing well and occasioning relational behavior that is consistent with "I am having a really great time," "people here like me," and "I am happy" that participate within positive affective experiences. Midway through the dinner party, a person is observed making a disgusted face and suddenly observational behavior is oriented towards indicators that others are not having a good time. Relational responses consistent with "Everyone is having a miserable time," "No one here likes me," "I am feeling angry" begin to occur and are more consistent with the negative affective network, occasioning escape behavior like starting arguments with family members and eventually storming away from the dinner table. In this case, the negatively valanced network may operate at greater relational mass than the positive affective network, and in this case, a shift in relational and emotional experiencing can seem almost inevitable and may be consistent with a diagnosis of borderline personality disorder and bipolar disorder (Parker, 2014).

Emotional inertia may describe the potential interaction of relational coherence and relational mass, exhibiting effects analogous to gravity (*RF* in Equation 3). Consider the initial conditions of a higher-mass negative affective network that only slightly exceeds the mass of the positive affective network. Based on Equation 3, the behavior analyst may predict that ambiguous stimulus events will be more attracted to the negative affective network than the positive affective network, increasing the relational volume (Rv) of the network. Due to derivation effects described in the HDML, additional instances of this derived relation can further strengthen the negative affective network, increasing relational density ($R\rho$), and consequently, increasing relational mass (*Rm*, Equation 2). With the increase in relational mass (*Rm*) and consistent with Equation 3, the negative affective network becomes even more likely to attract ambiguous stimulus events, and the ROE-M functional unit may suggest an increase in orienting functions towards negative or aversive elements contained within the environment. This negative relational inertia would mirror the negative affective inertia observed in clients with depression and is theoretically consistent with the behavior phenomenon of negative scanning (Greening et al., 2014).

Finally, affective differentiation has been described as a protective factor predicting emotional well-being, and this repertoire has been broadly described as emotional intelligence (Palmer et al., 2002; Blasco-Belled et al., 2022). Described in the model proposed in the current article, emotional intelligence may describe elaborate and complex forms of relational responding to emotional experiences that are highly flexible, both resistant and persistent, and the able to change or adapt. In particular, the ability to notice one's emotional experience, including physiological changes, appraisals, and overt behavior urges and actions, can allow for utilizing alternative behavioral strategies that influence these ROE-M processes, especially when the immediate emotional response is undesirable. For example, an environmental context that evokes feelings of anger may result in physical or social violence towards another person; however, if a person can tact their experience as "feeling angry," and taught to employ other strategies like engaging in present moment awareness or defusion in the moment, then other response options like walking away from the event or clearly communicating one's feelings can become available.

More broadly, the research on affective dynamics makes clear that analyzing relational density and ROE-Ming as a behavioral unit in the moment is suboptimal relative to evaluating the temporal dynamics of relational density and ROE-Ming across time and space. That is, how these properties of relational responding react within an ever-changing context and evolve across time may provide even more information about emotional behaviors that are of interest for behavior analysts. Although the synthesized RDT-HDML model is highly speculative and theoretical, the inclusion of affective and relational dynamics is even more so. Therefore, this analysis could be used to guide future conceptual developments and technologies used to capture temporal dynamics within a functional analytic framework.

Summary

The present article provides a conceptualization of the interplay between relational framing within broader psychological theories of affect and emotion. This conceptualization is intended to inform future research and clinical practice that seeks to functionally analyze emotional experiencing as a dynamic interplay between relational behavior, physiological responses, and overt actions, that operate within a motivational, attentional, and consequated context. The law of scientific parsimony dictates that simpler explanations are preferred; however, an explanation can only be as simple as needed to fully explain the phenomenon of interest. In the context of human language, cognition, and emotion that are involved in emotional experiencing, the phenomenon is vastly complex, necessitating an analysis that is sufficiently complex to predict it—to develop technologies needed adequate to influence it. Mental health and suffering within emotional experiencing is highly prevalent, and emphasizing emotion and other private experiences is becoming more commonplace within behavior analytic interventions, and predominant within the third wave of behavior therapy; yet, there appears to be a growing divide between the approaches used within ACT and other behavior therapies, and the actual behavior processes demonstrated within relational responding (Harte et al., 2023).

RDT and the HDML were developed to address the shortcomings within traditional RFT conceptualizations that focused on smaller relational classes, relatively simplistic training arrangements, and the use of unfamiliar stimuli with little influence on real world experiencing (Dixon et al., 2018). The IRAP provided a method to capture relational responding in flight even when relations were implicit and emotionally valanced. RDT expanded the concept of differential response strength toward a theoretical extension of RFT that described nonlinearity within higher-order relational patterns, and research from this theoretical extension are emerging at both the translational and applied levels, in areas of immense social importance (e.g., experiences of college students, racism, sexism, climate change). The HDML, building from the DAARRE model and research on the IRAP, introduced a framework that significantly broadens the scope and depth of RFT conceptualization of complex relational framing, and may be made even more precise through the integration of RDT. Predictions are evident across the levels of the HDML based on the volumetric-mass-density equations within RDT that are directly testable. Whether these predictions hold as stated is an empirical question and one worth exploring, and the empirical journey will inevitably bring with it significant changes and refinements to this initial conceptualization. This is important work. It is no longer sufficient for behavior analysts to teach people to behave how they want to behave, but to feel how they want to feel, and to experience how they want to experience in this life; and this is the ultimate pragmatic truth criterion of a behavior analysis of affect and emotion.

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Declarations

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