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# Emotion Regulation Strategy Use and Forecasting in Response to Dynamic, Multimodal Stimuli

William J. Mitchell<sup>1</sup>, Joanne Stasiak<sup>2</sup>, Steven Martinez<sup>1</sup>, Katelyn Cliver<sup>3</sup>, David Gregory<sup>1, 4</sup>, Samantha Reisman<sup>5</sup>, Helen Schmidt<sup>1</sup>, Vishnu P. Murty<sup>1, 6</sup>, and Chelsea Helion<sup>1</sup>

<sup>1</sup> Department of Psychology and Neuroscience, Temple University

<sup>2</sup> Department of Psychological and Brain Sciences, University of California, Santa Barbara

<sup>3</sup> Department of Psychological and Brain Sciences, Drexel University

<sup>4</sup> Perelman School of Medicine, University of Pennsylvania

<sup>5</sup> Department of Cognitive, Linguistic, and Psychological Sciences, Brown University

<sup>6</sup> Department of Psychology, University of Oregon

Successful emotion regulation (ER) requires effective strategy selection. Research suggests that disengagement strategies (e.g., distraction) are more often selected than engagement strategies (e.g., reappraisal) as emotional experiences intensify. However, the extent to which ER strategy *choice* in controlled circumstances reflects strategy *usage* during complex, multimodal events is not well understood. The present research uses dynamic, multimodal stimuli (i.e., a haunted house, horror movies) to examine the association between affective intensity and regulatory strategy usage among untrained participants—individuals given no prior regulation instructions or direction. Both a preliminary study ( $n = 54$ ) and Study 1 ( $n = 118$ ) failed to find relationships between emotional intensity and strategy usage to downregulate emotions as participants navigated a haunted house. Distraction was self-reported to be less successful than reappraisal at high intensities, contrary to expectations. Participants in Study 2 ( $n = 152$ ) forecasted regulation strategy usage based upon descriptions of emotionally regulated experiences from the preliminary haunted house study. Affective intensity predicted which strategies forecasters predicted they would use; though, forecasters overpredicted how often distraction was used in practice. Study 3 ( $n = 242$ ) incorporated strategy usage and forecasting within the same design by showing untrained participants video stimuli of varying intensity and capturing their regulatory responses. Forecasters again predicted using distraction more often than strategy users did in practice. Forecasters also overpredicted how effectively distraction reduced negative affective intensity relative to what strategy users reported. These results may highlight a disconnect between strategy fittedness when self-regulation occurs in uncontrolled, highly intense, or complex circumstances.


## Public Significance Statement

How individuals manage their emotions during dynamic, complex experiences is an important question for anxiety- and trauma-based disorder prevention and treatment. This study found distraction to be less effective than reappraisal at high negative emotional intensity in these difficult-to-regulate environments, which contrasts findings from relatively more controlled studies.

**Keywords:** emotion, self-regulation, naturalistic stimuli, decision making

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William J. Mitchell  <https://orcid.org/0000-0002-1198-9569>

Earlier versions of this article have been available on PsyArxiv (<https://osf.io/preprints/psyarxiv/23wtz>) since November 28, 2022. Posters containing some of these data and analyses have been presented at the 2021, 2022, and 2024 Society for Personality and Social Psychology Conference, as well as the 2022 Society for Affective Science Conference. A symposium containing these findings was presented during the 2024 annual conference of the Association of Psychological Science. Invited presentations using some of these data and analyses occurred in 2020 at the Temple University Motivational Behavior Seminar Series and in 2023 at the March Lab at Florida State University and Satpute Lab at Northeastern University. Stasiak et al. (2023) was published using physiological and emotion data from the

preliminary study. Cliver et al. (2024) was accepted for publication using memory data from the preliminary study and Study 1.

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*continued*

Overwhelming situations can generate profoundly intense emotions that often do not match our ideal emotional states. We can try to change our emotional responses in loud or crowded spaces, unexpected confrontations, and circumstances that we lack control over, but our ability to successfully regulate our emotions in these situations may be limited. A key factor in determining regulation efficacy is the strategy someone uses or chooses. Regulation strategy efficacy can be highly context-dependent, leading many to emphasize studying emotion regulation (ER) in different contexts as the next crucial direction for the field (Aldao, 2013; Dixon-Gordon et al., 2015; English et al., 2017; Rottweiler et al., 2018; Tang & Huang, 2019).

## The Process Model of ER

Foundational ER research (i.e., the process model) has identified categories of common strategies that people use to regulate their emotions (Gross, 1998). Characteristics of the regulator and the context can determine the effectiveness of these strategies (Young & Suri, 2020), and people often choose strategies to match their present circumstances (Opitz et al., 2015; Sheppes et al., 2011). For example, engagement strategies, like altering the meaning or interpretation of the emotion-eliciting stimulus (i.e., reappraisal), often have high cognitive demands. These can be contrasted against disengagement strategies, like diverting attention (i.e., distraction) or inhibiting the expression of emotion (i.e., suppression), which typically have relatively low cognitive demands (Sheppes & Gross, 2011).

How might these regulatory patterns be reflected in strategy choice? Although not explicitly directed to do so, the anticipation of a scary moment during a horror movie might prompt a person to look away from the screen (distraction), think about the actors in a different light (reappraisal), or limit the expression of their fear, all in an effort to reduce, or downregulate, an unwanted feeling. People in situations with few cognitive resources may compensate by selecting strategies that demand less cognitive effort according to the selection, optimization, and compensation hypothesis (Opitz et al., 2012). For example, if someone were watching a horror movie while they were tired or under high cognitive load, it may be easier to look away from the screen than to generate alternative, less fear-inducing reinterpretations by which to view the film's events. Attempting to reappraise would constitute a high-risk strategy in this context because it might be less likely to work (Ford & Troy, 2019) than a comparatively low-effort strategy like distraction.

This supposition is bolstered by the especially robust influence of emotional intensity upon strategy choice, as distraction is chosen more often (Hay et al., 2015; Orejuela-Dávila et al., 2019; Sheppes et al., 2011; Young & Suri, 2020) and is more effective

(Shafir et al., 2016) than reappraisal in response to high-intensity stimuli, at least in part because it can be deployed before relevant emotional information has been represented in working memory (Sheppes et al., 2014; Sheppes & Gross, 2011) and requires fewer cognitive resources (Dorman Ilan et al., 2019). This effect has been thoroughly replicated in lab studies and ecological momentary assessment (EMA) studies (Colombo et al., 2020; Heiy & Cheavens, 2014). However, this association may not readily translate to more complex, demanding, and less controlled environments (Sheppes, 2020), like that which we test directly here, due to differences in how we commonly measure and manipulate ER in these studies.

## External Validity in Extant ER Paradigms

Lab ER paradigms differ from the everyday experience of ER in a few key ways that may limit generalizability. Lab ER paradigms (e.g., Sheppes et al., 2011, 2014) usually train participants to use regulatory strategies before a task begins, which may prime more introspection and metacognition (Carver & Scheier, 1981) than what occurs in the typical ER experience. Lab ER paradigms also often necessarily show previews of emotional stimuli to allow participants to prepare their regulatory responses, but dynamic, high-intensity events in our everyday lives are often unexpected or difficult to anticipate. Following stimulus previews, lab ER paradigms also frequently prompt individuals to select a strategy, but aversive experiences in everyday life, like sharing the road with an erratic driver or being bullied, may not explicitly prompt the implementation of self-regulation.

Such study design decisions prioritize internal validity over external validity. Self-report capture of emotion in ER studies is often either assumed based upon standardized ratings associated with the stimuli (e.g., the International Affective Picture System picture set; Bradley & Lang, 2007), measured through unidimensional Likert scales (e.g., valence; Shafir et al., 2016), or is captured through established measures (e.g., the Positive and Negative Affect Schedule; Watson et al., 1988; Weiss et al., 2021). These approaches offer an efficient, reliable, and standardized means of assessing self-regulation but make assumptions about the emotional states of subjects that might not accurately reflect the complexity of emotional experience. As such, ER choice may more accurately reflect ER capacity than actualized ER behaviors (McRae & Gross, 2020). By relying upon these standardized manipulations, researchers are able to make a stronger causal claim regarding the relationship between emotion intensity and regulation, but this relationship appears complicated when the predictor is self-reported or disaggregated (Specker et al., 2024).

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Correspondence concerning this article should be addressed to William J. Mitchell, Department of Psychology and Neuroscience, Temple University, 717 Weiss Hall, 1701 N 13th Street, Philadelphia, PA 19122, United States. Email: billy.mitchell@temple.edu

EMA studies—another common means of studying ER—do more directly assess the external validity of ER strategy choice relationships by capturing emotionally evocative events within the everyday lives of trained research participants (e.g., Haines et al., 2016; Heij & Cheavens, 2014). However, most people are not trained to consider their ER strategies in their daily lives and are not prompted or primed to engage regulatory control before an emotional event occurs (Friedman & Gustavson, 2022). As such, training participants in these studies may also introduce important but often underappreciated deviations in regulatory behaviors from how untrained counterparts might respond in the same situation.

Contemporary constructivist theories posit that emotions are not fixed reactions but are instead shaped dynamically by cognitive and social processes, encompassing one's personal interpretations, beliefs, and social interactions (Lindquist et al., 2012). Study designs that prioritize external validity promote participant- or stimulus-level idiosyncratic experiences that are pivotal to developing working generative models of how the world around us works (Lee et al., 2021). Free-response capture may require fewer *a priori* assumptions from researchers about a participant's emotional experience than predetermined self-report options or standardized scales, thus reducing unintended researcher influence (Gendron et al., 2012; Lindquist et al., 2006) and improving generalizability (Miller et al., 2019). Applying natural language processing techniques to free-response data can improve our ability to capture the multifaceted, idiographic emotional experiences that constructivist frameworks emphasize (Mohammad, 2018) without sacrificing accuracy (Diamond et al., 2020) or quantifiability.

Research designs that incorporate more features of naturalistic regulation, such as not instructing or prompting participants to regulate (e.g., Heij & Cheavens, 2014; Opitz et al., 2015), often find people explore and flexibly apply multiple strategies that blur the boundaries of typical strategy classifications (Aldao & Nolen-Hoeksema, 2013; Ford et al., 2019; Heij & Cheavens, 2014; Opitz et al., 2015; Szasz et al., 2018). These approaches also capture meaningful variance in self-regulatory behaviors that more controlled designs cannot (Friedman & Gustavson, 2022; Kamradt et al., 2014; Malanchini et al., 2019). For example, overstimulation from complex, multimodal contexts may simultaneously be aversive and more cognitively demanding (i.e., better suited for disengagement strategies). However, attention may also be challenging to control in a context with so much attention-demanding stimuli, reducing the likelihood of observing the high-intensity-distraction association characterized in controlled laboratory studies (Draheim et al., 2022). Spontaneous or untrained ER in these contexts may rely more heavily on person-specific features, like habits, than on how emotionally arousing the situation may be (Christou-Champi et al., 2015; Koole et al., 2015; Norem, 2008). Yet, challenging situations may be precisely when adaptive regulatory control (i.e., the pattern between intensity and regulation choice observed in most laboratory studies) may be most valuable, as maladaptive ER tendencies predict more severe manifestations of posttraumatic stress disorders (Hannan & Orcutt, 2020) and related posttraumatic stress disorder outcomes (Specker & Nickerson, 2022). Thus, identifying whether the established association between intensity and effort-related strategy usage occurs in high-stress contexts is important for the development of potential interventions.

## The Present Study

We aimed to extend existing emotion regulation findings, such as Sheppes et al. (2011), by identifying possible boundary conditions in the relationship between affective intensity and regulation strategy behavior using three studies. Affective intensity is a prominent predictor of ER behavior (i.e.,  $r = 0.46\text{--}0.61$ ; “a very large effect size,” according to recent meta-analyses; Matthews et al., 2021), but the extent to which features of a dynamic, multimodal situation could overshadow this effect when experimental control is minimized remains unclear. As such, our study designs contrast previous research comparing reappraisal and distraction—the most popular strategy comparison in the literature (Heij & Cheavens, 2014)—by varying components of the designs that introduce greater complexity and/or ecological validity than traditionally might be present in similar studies.

Study 1 aimed to test whether this effect extends to unstructured, high-intensity circumstances by having participants with no prior ER strategy training or explicit direction to regulate (i.e., untrained) navigate a haunted house and report their undirected emotional and regulatory behaviors in a surprise recall task following the experience. To our knowledge, this represents the first attempt to study this relationship in an aversive, high-intensity, multimodal context using untrained participants. We additionally anticipated that participants experiencing high cognitive load in this environment would more often use distraction, in line with the effort according to the selection, optimization, and compensation hypothesis. Surprisingly, we did not find that intensity or cognitive load was associated with strategy usage. Efforts to minimize researcher bias, including the use of multiverse analyses and the use of normative affective ratings for haunted house experiences, also failed to find an association.

Study 2 aimed to determine whether participants would demonstrate typical ER behavior (i.e., a positive association between affective intensity and preference for distraction) when exposed to similar experiences as the haunted house but in a less dynamic, more controlled context. That is, we had people forecast or predict how they *would* regulate their emotions in the haunted house environment rather than experiencing the stimuli firsthand. Our goal was to retain some naturalistic features of Study 1 while introducing other features that mirror traditional lab studies. We hypothesized that subjects would forecast using distraction more often in response to descriptions of high-intensity regulated events and reappraisal more often in response to descriptions of low-intensity regulated events from the haunted house. We did observe the canonical association between emotional intensity and regulatory strategy selection with this design, though with an effect size smaller than the typical range found by Matthews et al. (2021). However, many study design differences between Studies 1 and 2 (e.g., real vs. simulated experience, emotion regulation usage vs. forecasting) limited our ability to make direct comparisons and draw conclusions about why those differences in outcome may have occurred.

To attempt to close this design difference gap in experience and self-regulation, Study 3 tasked untrained participants with watching videos of varying negative intensity and subsequently either reporting the regulatory strategies that they used (strategy usage) or the strategies that they predicted might be used (strategy forecasting) to downregulate their negative emotions. This study again featured greater experimental control than Study 1 but retained some of

Study 1 and Study 2 design features to promote ecological validity. For both strategy users and forecasters, increasing self-reported affective intensity predicted a greater likelihood of using distraction. However, forecasters were less likely than strategy users to use reappraisal at low intensities. A trend that emerged across all three studies was an inconsistency between how effective participants predicted distraction might be within these situations and how effective distraction was actually reported to be.

Together, these studies seek to determine the degree to which well-established regulatory patterns, such as the relationship between emotional intensity and strategy selection, replicate when environmental complexity is introduced. Methods and analyses supporting these findings are discussed.

### Study 1: Method

Study 1 tested whether the emotional intensity of negatively valenced events was associated with the likelihood of using a low-effort or high-effort regulatory strategy in a dynamic, feature-rich setting with an untrained sample of participants. To assess emotional intensity, participants performed a surprise free recall task immediately after exposure during which they self-reported the emotions they experienced via free response and the intensity of those emotions during self-selected events from the haunted house. Participants also noted the direction of their regulation attempts (i.e., upregulation, downregulation, no regulation), how effective those regulation attempts were, and the means by which they attempted to regulate in their own words. Haunted house experiences have been used with marked success in recent research to study emotion and self-regulation (Clasen et al., 2019; Stasiak et al., 2023; Tashjian et al., 2022). While haunted houses only represent a small proportion of the variability that emotionally relevant experiences could materialize as, they nonetheless offer safe and consistent but high-arousal events to elicit a wide range of emotional experiences (i.e., positive and negative emotions), intensities, and responses (i.e., regulation behaviors). This variance would be difficult to generate in a complex multimodal context outside of the lab while offering the same level of safety to the participants and control to the researchers. We report how we determined our sample size, all data exclusions, all manipulations, and all measures in the study.

### Participants

#### Preliminary Study

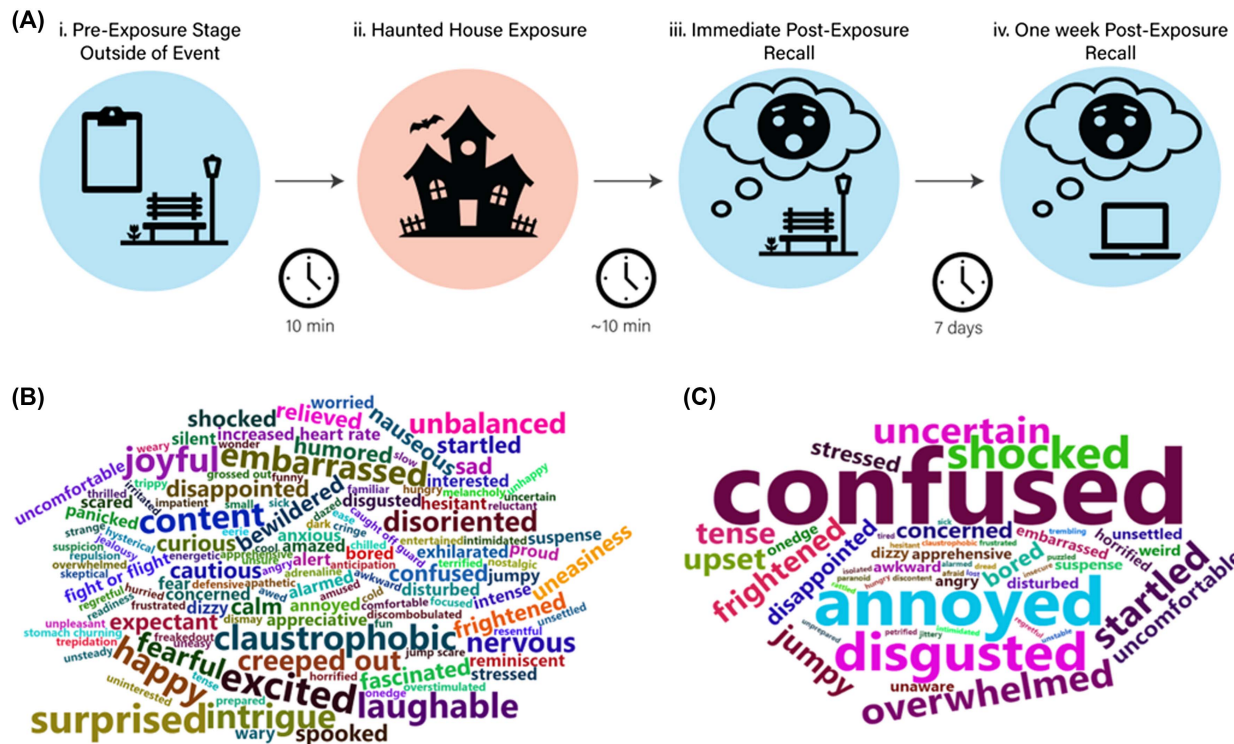
A preliminary study was conducted in October 2019 consisting of 54 participants (age:  $\bar{x}_{\text{age}} = 24.22$  years, range = 18–34 years,  $SD_{\text{age}} = 3.97$  years; gender: 26 female, 27 male, one nonbinary; ethnicity: 18.51% Hispanic, 81.49% not Hispanic) who were recruited from a large northeastern city via flyers for an Institutional Review Board (IRB)-approved fear and memory study. This study aimed to characterize the memory of Cliver et al. (2024) and physiological responses to Stasiak et al.'s (2023) high-intensity, naturalistic events. However, this preliminary study was also designed to allow us to determine the distribution of ER strategy usage in this context and determine a more appropriate sample size for our primary study, as a review of the extant literature did not yield analogous study designs within the ER space. A priori power

analyses for this preliminary study were conducted using the smallest effect size reported by Sheppes et al.'s (2011), examination of emotional intensity and regulatory choice ( $\eta_p^2 = 0.43$ ). Using “WebPower” (Zhang & Mai, 2019) in R 3.6.1 (R Core Team, 2022), we determined 18 participants would sufficiently power our main effect in a typical lab context. Given the additional complications our study design introduces which would likely reduce the effect size between our variables of interest and the resources we had available, we surmised a sample of 54 participants, three times the minimum sample size, might be sufficient to identify an effect. This analysis failed to find a statistically significant association between affective intensity and strategy usage, but our best-performing multilevel binary logistic regression model ( $\text{strategy} \sim \text{intensity} + [1 | \text{Participant}]$ ), as determined by an Akaike information criterion (AIC) comparison information theoretic approach, produced an odds ratio of  $OR = 1.83$  (95% CI [0.65, 3.2],  $p = .079$ ; see Supplemental Materials for more preliminary study design and analyses details). This observed model from the preliminary study was used to generate an a priori power curve for Study 1 via “simr” (Green & MacLeod, 2016) in R 3.6.1, which estimates the proportion of simulated data sets in which the null hypothesis is rejected given the target model. This approach to calculating power is preferable for hierarchically structured data because it does not assume independence of observations. We determined that at least 76 participants with an average of three observations each (228 observations total) would be required to sufficiently power our study based upon simulations with the observed data (two-tailed,  $\alpha = .05$ ,  $1 - \beta = 0.80$ ,  $Pr(Y = 1|X = 1) H_0 = 0.615$ ). We increased the target sample size to 120 participants due to attrition concerns and the needs of the concurrently run experiment on fear and memory (Cliver et al., 2024). However, we were only able to recruit 98.33% of our recruitment goal due to time constraints (i.e., all data collection must occur before the haunted house closes for the season).

#### Study 1

In October 2021, 118 participants (age:  $\bar{x}_{\text{age}} = 20.80$  years, range = 18–34 years,  $SD_{\text{age}} = 2.87$  years; gender: 73 female, 40 male, five nonbinary) were recruited from a large northeastern city via flyers for an IRB-approved study on fear processing at a local haunted house attraction. A description of Study 1's design is illustrated in Figure 1A. Eligible participants were native English speakers between the ages of 18 and 35, had normal or corrected-to-normal vision, were not pregnant, had no history of seizures, cardiovascular issues, or neurological disorders, could comfortably walk for at least 1 hr, and had not been to this haunted house in the past. On average, participants were more educated ( $\bar{x}_{\text{years of education}} = 16.90$  years,  $SD_{\text{years of education}} = 2.75$  years) than the average U.S. adult who, according to the U.S. Census Bureau's American Community Survey, has completed 13.7 years of education. Categorically, 81.9% reported having completed some college (58.6%), a 4-year degree (12.9%), some postgraduate studies (03.4%), or a postgraduate degree (06.9%). Socioeconomic status was slightly negatively skewed, with 14.5% of respondents reporting making less than \$15,000 per year, 07.7% reporting between \$15,001 and \$25,000, 07.7% reporting between \$25,001 and \$35,000, 05.1% reporting between \$35,001 and \$50,000, 22.2% reporting between \$50,001 and \$75,000, 12.8% reporting between \$75,001 and \$100,000, 17.9%



**Figure 1***Study 1 Task Overview*

*Note.* (A) Study 1 Task Overview: One hundred eighteen participants navigated a haunted house in small groups. (i) Before entering, participants completed baseline questionnaires. (ii) Participants entered the haunted house, which took approximately 37 min to complete. (iii) Afterward, participants immediately recalled three events from the haunted house and their attempts to regulate them. (iv) In an online follow-up, participants again recalled the initial three events and additionally described six new events. (B) Frequency-weighted word cloud of all emotions endorsed by participants during Study 1, illustrating the range and prevalence of reported emotions. (C) Frequency-weighted word cloud of negatively valenced emotions specifically targeted for downregulation through reappraisal or distraction strategies. See the online article for the color version of this figure.

reporting between \$100,001 and \$150,000, and 12.0% reporting greater than \$150,000. The racial and ethnic identities of participants were not assessed. Participants were compensated \$60.00 in Visa debit cards.

## Materials and Procedure

### Preexposure

Participants reported to a provisional headquarters (i.e., tent, tables, chairs, computers) constructed just outside the haunted house property to complete individual difference questionnaires, questionnaires assessing prior knowledge of the haunted house, expectations, and motivations for participating, as well as a measure of cognitive load. To assess prior knowledge, participants indicated the number of times they had attended other haunted houses, how much information they felt they knew about this specific haunted house, and from which sources had they learned information about this specific haunted house (e.g., advertisements, friends, news reports). To assess expectations, participants were asked how much positive and negative emotion they anticipated experiencing prior to exposure on a 5-point Likert scale. Labels for the 5-point Likert

scales included “none at all,” “a little,” “a moderate amount,” “a lot,” and “a great deal.” Participants were also asked how fearful they felt, how sensitive they were to startling stimuli, how much they enjoyed haunted houses, and how much they enjoyed feeling fear (all assessed on Likert scales). Motivations to participate were assessed using 100-point sliding scales and included payment, thrills, novel experiences, challenges, social pressure, scientific interest or duty, and boredom. The poles and central position were labeled as “not at all motivating,” “moderately motivating,” and “extremely motivating.” Cognitive load was assessed prior to exposure, immediately after exposure, and at a later follow-up using a 15-item Remote Associates Test (RAT). Forty-five RAT items were selected for their difficulty as measured by Bowden’s 15-s trials, such that each item had two equally difficult counterparts that could be randomly assigned across the three time points (Bowden & Jung-Beeman, 2003). Following instructions, participants completed three practice trials with feedback. During the RAT task, participants had 15s to identify the target word and did not receive feedback. Participants were then fitted with heart rate monitors and escorted to the haunted house entrance. All preexposure questionnaires and materials are available within our OSF repository (see [https://osf.io/j5sku/?view\\_only=89d87669e7674096819c439ca109c483](https://osf.io/j5sku/?view_only=89d87669e7674096819c439ca109c483)).

## Exposure (Haunted House)

Participants experienced the haunted house in 31 groups across 11 nights ( $\bar{x}_{\text{size}} = 3.81$  participants;  $SD_{\text{size}} = 1.12$  participants). This specific haunted house was chosen because (a) it uses professional actors renowned for eliciting a range of affective responses; (b) it contained four themed sections designed to be either low intensity or high intensity, each with a unique esthetic providing variability to the stimuli; (c) it provides a remarkably consistent experience across sessions; and (d) coordination with the facility granted us special privileges to use equipment (i.e., computers, heart rate monitors) and better guarantee consistency across exposures (i.e., entering before other guests, keeping groups together).

Participants received minimal instructions to promote ecological validity. Participants were to walk through the haunted house in a single-file line and avoid sharing thoughts, reactions, and experiences with other participants. Limiting communication prevented participants from skewing each other's memories and perceptions of the events before they could be recorded. Participants were encouraged to act and react as naturally as possible without interacting with each other (i.e., grabbing, holding, touching). While verbal and physical social support are recognized and effective forms of emotion regulation, they were beyond the purview of this study's focus, which was based upon common process model strategies. However, perceptions of social support were captured after exposure to assess their potential effect upon our outcomes of interest. As part of a concurrently run memory experiment, some participants ( $n = 58$ ) did receive additional instruction to navigate specific sections as if they would later have to complete a memory test or write a review of that section. However, these groups did not statistically differ significantly from the control group in reported affective intensity,  $F(2, 81) = 1.41, p = .25$ ; regulation strategy usage,  $F(2, 73) = 0.05, p = .95$ ; or regulation strategy success,  $F(2, 81) = 1.93, p = .15$ , as determined by analysis of variance. The data relevant to this memory experiment are beyond the purview of this study and are better captured within another forthcoming article. The accompanying research assistant led the group through each section. The approximate exposure time was 37.4 min.

## Postexposure

Following exposure, participants completed immediate postexposure assessments at a remote site outside of the haunted house. Participants were tasked with identifying three emotionally salient events that occurred from a randomly selected haunted house section and reporting affective and regulatory details of that event. Events from other haunted house sections were not tested during the immediate exposure session to avoid conflicts with the aforementioned concurrently running memory experiment. Participants were not trained in ER strategies, nor were they primed to consider their ER strategies prior to these questionnaires. Though experiential sampling methods and EMAs are often applied in naturalistic settings to capture moment-to-moment fluctuations in emotion and regulation with considerable success (see Colombo et al., 2020; Shahane et al., 2023), we chose postexposure assessments as our means of assessment in part for the following reasons: (a) Assessing participant reactivity midexposure can lead participants to alter their affective and regulatory behaviors in response to the assessment prompts (Stone et al., 2003); (b) training participants to use

experiential sampling methods or EMA technology effectively in this context would require training in ER strategy categorization in violation of the goals of this study; and (c) the use of such technology during exposure would violate the immersive, high-intensity nature of the context (Shiffman et al., 2008). Furthermore, studies that have used cued recalls to capture ratings of emotional experiences after exposure have found high consistency between experience and recall (Hutcherson et al., 2005; Levenson & Gottman, 1983). For each of the three events, participants wrote a detailed description of what occurred. Participants then noted which emotions (up to a total of five) they felt during this event via free response. Participants rated how intense their emotion felt ("During [this event], how intense was the [emotion] you experienced?") on a 5-point Likert scale (labels included, in order of increasing intensity: "none at all," "a little," "a moderate amount," "a lot," and "a great deal"). Participants were also tasked with describing how they tried to regulate each emotion, if at all ("Did you attempt to reduce or intensify this [emotion]?"), via free response ("Please describe how you attempted to reduce or intensify this [emotion]"). People's accuracy in recalling details of similar real-world experiences via free response was surprisingly high in recent investigations using similar methodology (Diamond et al., 2020). Participants were also asked directly whether they attempted to downregulate or upregulate their experiences, how successful their regulatory efforts were, and regulatory responses were assessed in response to each emotion rather than each event. Thus, rather than exploring this phenomenon at the event level, which might require regressing the probability of using a strategy upon the average intensity of all emotions experienced in that event—an assumption we would not make in confidence—we draw associations between regulation strategy usage and the emotions that participants identify as directly motivating them. We refer to data captured at this time point as being "immediately reported." Following completion of immediate postexposure measures, participants were dismissed, instructed to not discuss their experiences, and to remain in contact with researchers for a follow-up session, which was conducted remotely (*time since exposure*:  $\bar{x}_{\text{delay}} = 7.01$  days;  $SD_{\text{delay}} = 0.91$  days) to assess how memory of self-regulation and memory accuracy in this context alters over time. At this delayed follow-up session, participants were tasked with identifying six additional events and their affective and regulatory responses to each.

## Strategy Usage Coding

During the preliminary study, two hypotheses-blind raters classified strategy descriptions into one or more strategy categories: reappraisal, distraction, suppression, situation selection, situation modification, or "none of the above" (interrater reliability [IRR] agreement = 0.880). Raters were also provided the participant's description of the event and the emotions they experienced, which they indicated having downregulated. Raters were undergraduate research assistants who trained by first reviewing examples of landmark literature that defined the strategies of interest as commonly used in the field (Gross, 1998, 2002). Raters then reviewed select methodological excerpts from experimental articles to see how cognitive reappraisal, attention deployment, and other process model strategies were defined within past studies (Shafir et al., 2016; Sheppes et al., 2011). Last, raters independently completed classification exercises using examples of regulation strategy

descriptions from the same context but which were collected during the preliminary study. Through the training and classification process, raters were instructed not to collaborate or discuss their ratings with each other during the rating process. After individually classifying each description, a moderator (W.M.) compared the ratings for disagreements (i.e., cases in which raters disagreed on how a regulation event should be classified). The moderator then met with both raters remotely using a digital video conferencing platform and moderated a review of the classifications, asking raters to compromise in cases of classification disagreement. The moderator's role was to facilitate discussion of classifications and document their conclusions but was not involved in the discussion and disconnected during them (i.e., muted their microphone; turned off camera) to avoid unduly influencing the outcome.

This approach revealed that distraction and reappraisal were by far the most commonly used strategies in this context. Of the 182 self-reported downregulated events recorded in the preliminary study, 30.7% used reappraisal and 61.5% used distraction, with the other three strategies (i.e., suppression, situation modification, situation selection) combined appearing in fewer than 20% of events (note that the total percentage sum is greater than 100% due to the occurrence of multistrategy experiences). Two hypotheses-blind raters classified each observation's strategy description in Study 1 into one or more strategy categories: reappraisal, distraction, suppression, a combination of the three, or none of the above (IRR agreement = 0.877). Situation modification and selection were excluded due to the infrequency of their use. Suppression was also used infrequently in Study 1 but was categorized by Study 1 raters due to its large presence within the broader literature. Raters were undergraduate research assistants who were trained using the same methodology described in the preliminary study but were not the same raters from the preliminary study. The training materials and instructions generated for this purpose have been made available within our OSF repository (see [https://osf.io/j5sku/?view\\_only=89d87669e7674096819c439ca109c483](https://osf.io/j5sku/?view_only=89d87669e7674096819c439ca109c483)).

### ***Event and Location Coding***

Prior to launching our study, a key was generated by research staff documenting each of the unique events contained within the haunted house, including detailed descriptions, their temporal order, and the approximate locations of each event. This key was used as a reference by two additional hypothesis-blind independent raters who had not experienced the haunted house. They identified the approximate locations of events reported by participants using the detailed descriptions that participants provided. Each event was labeled as occurring either within one of the four sections or as "not applicable" in cases of high ambiguity. Descriptions of the same event experienced by different subjects were identified and binned together. The training and rating process otherwise mirrored the procedure outlined for strategy usage coding. Agreement between raters was high (IRR = 0.918).

### ***Questionnaire Response Processing and Coding***

Emotion responses were processed by (a) removing entries lacking intelligible affective information (e.g., "-", "nothing," "idk man"); (b) removing unnecessary punctuation, hyphenation, and qualitative modifiers (e.g., "very sad" becomes "sad"); (c) splitting compound

emotion response (e.g., "sad/angry" becomes "sad" and "angry"); (d) correcting spelling errors according to the top suggestions recommended by R's native spell checking software; and (e) lemmatization (e.g., "annoyance," "annoying," and "annoyed" become "annoy"). These modified emotion responses were then merged with the National Research Council (NRC) lexicon, which contains over 20,000 English emotion words human-rated by valence, arousal, and dominance (Mohammad, 2018). Valence was determined using NRC lexicon valence scores. Observations without an associated NRC lexicon entry were dropped due to lack of valence data.

### ***Analysis***

To explore our primary question, the effect of emotional intensity upon regulatory strategy usage, we specified mixed effect binary logistic regressions accounting for the random effect of participants using the "lme4" package (Bates et al., 2015) in R (R Core Team, 2022) and followed an information theoretic approach via AIC comparison, which prioritizes model parsimony and penalizes models with excessive variables.

This observational approach, using the idiographic self-reported emotional intensity of each subject to predict regulation behaviors, differs substantively from its experimentally controlled predecessors, which instead generally manipulate emotion using standardized stimuli sets and use the standardized intensity of each stimulus as the predictor of strategy choice rather than the intensity subjects experienced. Such an approach assumes that, over a sufficiently large sample, the average experienced intensity of any given stimulus will match the standardized value for that stimulus. In exchange for making this assumption, researchers likely reduce potential confounds and are better able to address causality. By taking the observational idiographic approach that we had, we assume that the personal experiences reported represent emotion preregulation, though it may be the case that these reports were also influenced by postregulation emotion. While pre- and postregulation emotion intensities appear highly correlated (Specker et al., 2024), important differences may be obfuscated. By not making the same assumptions as more experimentally controlled studies, our analytic approach seeks a pragmatic understanding of the relationship between intensity and emotion regulation, accepting potential confounds as they may naturally co-occur and aiming to determine whether the relationship exists without the degree of experimental control that prior studies established.

All data and scripts used to produce this analysis are publicly available at OSF (see [https://osf.io/j5sku/?view\\_only=89d87669e7674096819c439ca109c483](https://osf.io/j5sku/?view_only=89d87669e7674096819c439ca109c483)). Preregistration for Study 1 methods and hypotheses is publicly available at AsPredicted ([https://aspredicted.org/DP1\\_453](https://aspredicted.org/DP1_453)).

### ***Study 1: Results***

A subset of 298 observations in which a negative emotion was downregulated by either distraction or reappraisal was used for analyses related to our primary hypothesis. These observations were reported by 77 participants. Of the 298 total observations, 175 (58.72%) reported using distraction to regulate their emotions. The average emotional intensity of observations was 2.41 (range = 0–4,



$SD = 0.932$ ). Figure 1B illustrates the variance in all emotions, and Figure 1C illustrates the emotions endorsed within the data set of 298 observations.

### Thrill-Seeking Motivated Study Participation

Although horror attractions may feature aspects of emotional experiences that are difficult to capture in more traditional paradigms, they may have limitations as well. For example, such a setting may generate self-selection biases in our sample. To monitor this, participants were asked about their expectations and motivations to participate in this study. Participants were asked how much they enjoyed fear on a 0 to 6 scale, with the average response sitting above the midpoint of the scale ( $\bar{x} = 3.40$ ,  $Mdn = 4$ ,  $SD = 1.82$ ). Participants were also asked, “To what extent are the following items motivating your participation?” on a 0 to 100 scale with items including the payment received for participating ( $\bar{x} = 59.2$ ,  $Mdn = 59$ ,  $SD = 31.1$ ), the thrills they may feel in the haunted house ( $\bar{x} = 63.3$ ,  $Mdn = 73$ ,  $SD = 31.7$ ), the opportunity for new experiences ( $\bar{x} = 70.1$ ,  $Mdn = 78$ ,  $SD = 28.0$ ), the opportunity for challenging experiences ( $\bar{x} = 53.3$ ,  $Mdn = 50$ ,  $SD = 30.3$ ), social pressures ( $\bar{x} = 15.5$ ,  $Mdn = 02$ ,  $SD = 25.7$ ), a desire to help science ( $\bar{x} = 59.4$ ,  $Mdn = 58$ ,  $SD = 29.9$ ), and boredom ( $\bar{x} = 28.0$ ,  $Mdn = 15$ ,  $SD = 31.4$ ). Thrill-seeking motivations strongly correlated with fear enjoyment ( $r = 0.582$ ,  $p < .001$ ), and Bonferroni-adjusted contrasts did determine that thrill-seeking as a motivation was significantly greater than boredom,  $t(144) = 7.17$ ,  $p < .001$ ; social pressure,  $t(144) = 9.70$ ,  $p < .001$ ; and the pooled average of all motivations,  $t(504) = 4.19$ ,  $p < .001$ ; but not challenge-seeking,  $t(144) = 2.05$ ,  $p = .289$ ; novelty-seeking,  $t(144) = -1.38$ ,  $p = 1.000$ ; payment,  $t(144) = 0.84$ ,  $p = 1.000$ ; or science participation,  $t(144) = 0.81$ ,  $p = 1.000$ . This may suggest that our participants were slightly higher in thrill-seeking motivations relative to what we might expect to find in an average population.

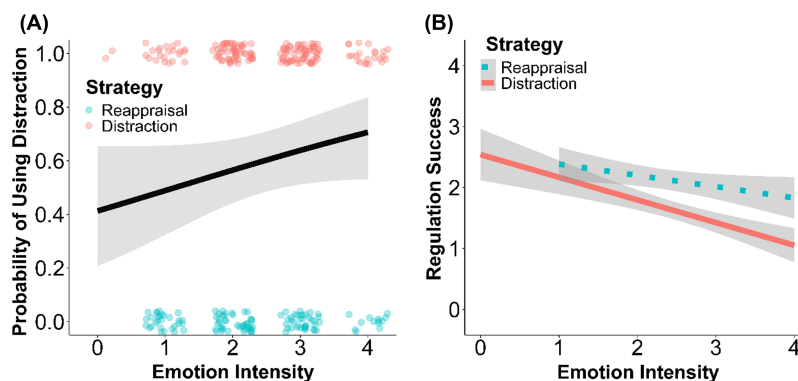
### Study Participants Regulated Their Emotions Without Prompt

Another limitation may be a lack of motivation to self-regulate. Because haunted houses are entertainment, participants may be less inclined to self-regulate, regardless of which strategy they use. Within the preliminary study, we found a positive association between state anxiety measured immediately before the haunted house and the average extent to which participants attempted to regulate their emotions (assessed through the question, “To what extent did you attempt to change or regulate how you felt during this event?”) across events ( $\beta = 0.34$ , 95% CI [0.054, 0.626],  $p = .021$ ), as well as a positive association between the average negative affective intensity of an event and extent to which participants attempted to regulate their emotions during that event ( $\beta = 0.31$ , 95% CI [0.17, 0.46],  $p < .001$ ; see Supplemental Materials for more preliminary study design and analyses details). Both suggest, as expected, that participants within this setting experiencing negative emotions do self-regulate these emotions without researcher prompting. Self-regulation extent or efforts were not assessed within Study 1 to reassess this relationship.

### Intensity Did Not Predict Regulatory Strategy Usage

To test our primary hypotheses, models using either z-scored emotional intensity or person-centered emotional intensity as the primary predictor were constructed iteratively (i.e., adding one fixed effect to the model at a time), but across all model comparisons, no model performed better than our null model, which did not feature any fixed effects (intraclass correlation coefficient [ICC] = 0.40). Our best-performing nonnull model—including only intensity as a fixed effect ( $p = .10$  when compared to null)—did not find a relationship between emotional intensity and strategy usage ( $OR = 1.36$ , 95% CI [0.95, 1.95],  $p = .10$ ; Figure 2A). An odds ratio of 1.36

**Figure 2**  
*Emotional Intensity, Strategy Choice, and Regulation Success*



*Note.* (A) Across tested mixed-effects binary logistic regression models, emotional intensity did not significantly predict strategy usage. Shown here is the model using emotional intensity ( $M = 2.41$ ,  $SD = 0.932$ ) to predict the choice between reappraisal and distraction for regulating negative emotions. (B) Strategy moderated the relationship between emotional intensity and regulation success ( $\beta = 0.25$ ,  $p = .003$ ). While reappraisal success remained relatively stable across emotional intensities, distraction showed a negative association with increasing emotional intensity, contrary to what extant literature might suggest. See the online article for the color version of this figure.

suggests that for every one standard deviation unit increase in emotional intensity, the odds of choosing distraction to regulate increase by approximately 36%, but importantly, this association is not statistically significant and markedly smaller than what might be observed in more controlled strategy-selection paradigms. As such, we did not find strong evidence to support that emotional intensity predicts strategy usage in this dynamic, high-intensity setting.

### Multiverse Approach Also Failed to Explain Strategy Usage

We expanded the scope of our primary analyses and conducted additional exploratory analyses to determine whether a stronger association between strategy usage and affective intensity could be found using different inclusion criteria, comparing engagement strategies (i.e., reappraisal) to disengagement strategies (i.e., suppression, distraction) as defined in the broader literature (e.g., Dixon-Gordon et al., 2015), and including contrahedonic regulation activity (i.e., downregulating positive emotion). We found only a single model that surpassed nominal statistical thresholds of significance in model fit ( $ICC = 0.37$ ;  $p = .04$  when compared to null), but that did not maintain significance after adjusting to maintain a family-wise error rate ( $p = .32$ ). Details and results of this analysis can be found in the Supplemental Materials.

### Manipulated Emotion Intensity Did Not Predict Regulation Strategy Usage

Although we lack explicit standardized ratings for each event within the haunted house, each section was designed to either elicit low- or high-intensity emotional reactions. As such, by specifying the intensity category of the section in which each event occurred as a predictor predicting regulation outcome, we were able to conduct another exploratory analysis with a design that imperfectly but more closely resembled the emotion manipulation exhibited in lab studies. A paired  $t$  test—using ratings of fear that subjects self-reported on a 5-point numeric scale after each section during exposure—confirmed that subjects experienced the high-intensity sections with significantly more fear than the low-intensity sections,  $\bar{x}_{\text{high}} = 3.38$ ,  $\bar{x}_{\text{low}} = 1.90$ , 95% CI [1.35, 1.61],  $t(235.0) = 22.9$ ,  $p < .001$ . The same trend was observed when using the self-reported intensity of individuals' emotions reported by subjects in a Welch's  $t$  test, though it fell short of statistical significance,  $\bar{x}_{\text{high}} = 2.41$ ,  $\bar{x}_{\text{low}} = 2.18$ , 95% CI [−0.02, 0.48],  $t(47.6) = 1.82$ ,  $p = .075$ . Using a Pearson's chi-square test with Yates' continuity correction, we again found no association between the categorical intensity of the section in which each event occurred and the regulation behavior that followed each event,  $\chi^2(1, N = 231) = 0.002$ ,  $p = .964$ . Among events in low-intensity sections, 40% were regulated via reappraisal, and 60% were regulated via distraction. Among high-intensity section events, 42.7% of events were regulated via reappraisal, and 57.3% of events were regulated via distraction. Although this approach is low in resolution, it at least suggests that this null relationship is not simply because our hypothesized predictor

(i.e., self-reported emotion intensity) is a product of, rather than a precursor to, self-regulation.

### Aggregate Emotion Intensity Did Not Predict Regulation Strategy Usage

One means of approximating normative ratings for events in the haunted house may be to take a “leave-one-out” approach to emotion intensity. With this technique, the downregulation behavior of each observation is regressed upon the average negative emotion intensity reported by all other participants who experienced and reported that same event. Excluding each subject's self-reported emotion intensity yields a predictor that is independent from the outcome, mirroring the relationship between standardized stimulus ratings and emotion regulation choice in more controlled settings. Two hundred ninety (290) observations were described well enough by subjects to be reliably categorized by our independent raters as one of 36 unique events that subjects experienced within the haunted house. Twenty-four of the 36 unique events were reported by two or fewer participants and excluded from this analysis to ensure enough observations for a mean rating to be calculated ( $\bar{x}_{\text{obs}} = 9.92$ ,  $Mdn_{\text{obs}} = 8.0$ ,  $SD_{\text{obs}} = 6.76$ ,  $maximum_{\text{obs}} = 22$ ). We conducted an additional analysis excluding any event with fewer than five observations as well to be more conservative in our aggregation (events = 7,  $\bar{x}_{\text{obs}} = 14.3$ ,  $Mdn_{\text{obs}} = 13.0$ ,  $SD_{\text{obs}} = 5.5$ ,  $maximum_{\text{obs}} = 22$ ). Because emotions captured in our study were multidimensional (i.e., subjects could report intensities for multiple emotions for each event), we also took two approaches to compute aggregate ratings: using the average of all emotion intensities that a subject reported for any given event and using the maximum of all emotion intensities that a subject reported for any given event. At a minimum of three observations per event, a mixed-effects binary logistic regression did not find ratings computed using either approach to predict regulation usage (maximum:  $OR = 1.20$ , 95% CI [0.21, 7.03],  $p = .96$ ;  $M$ :  $OR = 1.43$ , 95% CI [0.17, 12.40],  $p = .96$ ). A null effect was also observed using a more conservative five-observation minimum (maximum:  $OR = 0.52$ , 95% CI [0.06, 15.30],  $p = .96$ ;  $M$ :  $OR = 0.91$ , 95% CI [0.04, 23.8],  $p = .96$ ). This exploratory analytic approach is of a higher resolution than our analysis using section as a predictor and came to the same conclusion as our other analyses. However, this approach may also be underpowered due to excluding ambiguous observations and events with too few analogous observations.

### Cognitive Load Did Not Predict Regulatory Strategy Usage

The association between strategy choice and cognitive load has been well documented in the literature (Dorman Ilan et al., 2019), but attempts to replicate it beyond lab settings have been limited. Given the high-intensity, often overwhelming nature of this setting, we had preregistered the hypothesis that cognitive load should demonstrate a positive association with the probability of using distraction as an ER strategy. However, we failed to find evidence that cognitive load postexposure—as assessed by the RAT test—predicted strategy usage during exposure ( $b = -0.02$ , 95% CI [−0.044, 0.010],  $p = .21$ ), even when adjusting for

baseline cognitive load as assessed both prior to exposure and 1 week later.

### Nuisance Variables Did Not Predict Regulatory Strategy Usage

In addition to our primary analyses, we evaluated the impact of several nuisance variables. These are variables that, according to existing research, might confound the relationship between affective intensity and strategy usage but were not of primary theoretical focus for these experiments. Examples measured in this study include emotion expectations (Denny et al., 2014), motivations to participate (Tamir, 2016), attitudes toward fear and haunted houses (Argyriou & Lee, 2020), participant sex (McRae et al., 2008), age (Blanchard-Fields et al., 2004), depression (Beck Depression Inventory–II), anxiety (State–Trait Anxiety Inventory), intolerance of uncertainty (Intolerance of Uncertainty Scale [IUS]; Aldao et al., 2010), regulation tendencies (Emotion Regulation Questionnaire [ERQ]; Gross & John, 2003), time of day, and presence of peers.

We did not find significant associations between the proportion of events in which distraction was used and how positively ( $b = 0.035$ , 95% CI  $[-0.032, 0.102]$ ,  $p = .30$ ) or negatively ( $b = 0.047$ , 95% CI  $[-0.017, 0.112]$ ,  $p = .14$ ) participants expected to feel during the study. We also did not find an association between distraction versus reappraisal usage and the motivations cited for participation, including payment ( $b = -0.000$ , 95% CI  $[-0.003, 0.002]$ ,  $p = .629$ ), thrill-seeking ( $b = -0.000$ , 95% CI  $[-0.003, 0.002]$ ,  $p = .801$ ), novelty-seeking ( $b = 0.001$ , 95% CI  $[-0.002, 0.004]$ ,  $p = .454$ ), peer influence ( $b = 0.001$ , 95% CI  $[-0.002, 0.003]$ ,  $p = .595$ ), boredom ( $b = -0.001$ , 95% CI  $[-0.004, 0.001]$ ,  $p = .341$ ), contributing to science ( $b = 0.000$ , 95% CI  $[-0.002, 0.002]$ ,  $p = .858$ ), and seeking a challenge ( $b = 0.000$ , 95% CI  $[-0.003, 0.002]$ ,  $p = .935$ ). We additionally did not find any associations between distraction usage and how much participants self-reported enjoying fear ( $b = -0.012$ , 95% CI  $[-0.050, 0.027]$ ,  $p = .55$ ) or haunted houses ( $b = 0.021$ , 95% CI  $[-0.024, 0.066]$ ,  $p = .35$ ), participant sex,  $t(73) = 1.54$ , 95% CI  $[-0.029, 0.225]$ ,  $p = .13$ ; age ( $b = 0.000$ , 95% CI  $[-0.024, 0.023]$ ,  $p = .98$ ); depression ( $b = -0.004$ , 95% CI  $[-0.024, 0.016]$ ,  $p = .70$ ); anxiety ( $b = 0.000$ , 95% CI  $[-0.009, 0.008]$ ,  $p = .97$ ); intolerance of uncertainty ( $b = 0.000$ , 95% CI  $[-0.005, 0.006]$ ,  $p = .92$ ); tendency to use reappraisal ( $b = 0.000$ , 95% CI  $[-0.012, 0.013]$ ,  $p = .97$ ) or suppression ( $b = 0.002$ , 95% CI  $[-0.011, 0.015]$ ,  $p = .76$ ); time of day,  $F(2, 73) = 0.04$ ,  $p = .96$ ; presence of familiar peers,  $t(60) = -0.40$ ,  $p = .700$ ; or which group participants traversed the haunted house with,  $F(30, 45) = 0.93$ ,  $p = .57$ . Despite the lack of association, these variables were included as covariates in some models as part of our subsequent multiverse analysis.

### Regulatory Strategy Usage and Intensity Interact to Predict Regulatory Success

Following our emotional intensity analyses, we explored how strategy usage moderated the relationship between intensity and success, as using distraction during high-intensity emotional states should more successfully regulate emotions than using reappraisal (Sheppes et al., 2011). After constructing a series of multilevel linear models and again following an information theoretic approach, we found that our best-performing model did indeed include an

interaction between strategy usage and emotional intensity ( $ICC = 0.42$ ,  $p = .003$ ) and found that interaction to be significant ( $\beta = 0.25$ , 95% CI  $[0.09, 0.42]$ ,  $p = .003$ ). However, a simple slopes analysis revealed a surprising finding: no relationship was observed between regulatory success and emotional intensity for events regulated via reappraisal ( $\beta = -0.03$ , 95% CI  $[-0.16, 0.10]$ ,  $p = .70$ ), but regulatory success was *negatively* associated with emotional intensity for distraction-regulated events ( $\beta = -0.28$ , 95% CI  $[-0.40, -0.16]$ ,  $p < .001$ ; Figure 2B). When respecifying the simple slopes analysis to designate intensity as the moderator, we find that reappraisal was self-reported as significantly more successful than distraction at high ( $\beta = -0.676$ , 95% CI  $[-0.975, -0.377]$ ,  $p < .001$ ) and average ( $\beta = -0.447$ , 95% CI  $[-0.667, 0.227]$ ,  $p < .001$ ) intensities, but not low ( $\beta = -0.218$ , 95% CI  $[-0.508, 0.072]$ ,  $p = .141$ ) intensities. In traditional, experimentally controlled paradigms, we often observe distraction to be more effective than reappraisal at high emotion intensity (Sauer et al., 2016; Specker et al., 2024). These data seem to document a deviation—that distraction appeared to be less—not more—successful than reappraisal—from this pattern when utilizing an observational, idiographic methodology in a high-intensity, quasinalistic setting, though an important caveat is that we are capturing *subjective* assessments of success and not assessing success via measurement of intensity attenuation.

### Study 2: Method

A preliminary study and Study 1 both failed to find an association between affective intensity and strategy usage in a complex, high-intensity, multimodal environment using untrained, undirected participants, even when adjusting for noted moderators like cognitive load. Exploratory models found that the relationship may appear, albeit weakly, when including positive and negative emotions, but the effect did not survive adjustments for multiple comparisons. We also found that distraction may have been less successful at regulating higher intensity emotions than reappraisal in this specific circumstance—a surprising finding given the extant literature. However, the lack of experimental control limits interpretations of this null effect. We theorized that participants exposed to versions of the same stimuli could demonstrate ER patterns in line with the extant literature if made less complicated and given greater experimental control. Although using audiovisual recordings from the experience would have been ideal, we were unable to obtain permission to record such data during the previous studies. Instead, we generated decontextualized representations of preliminary study subjects' self-reported idiographic experiences with only the relevant information present (i.e., description of event, emotions felt, intensity of emotions) and asked a new sample of participants to simulate or forecast how they might self-regulate in the same circumstance given the information provided (events available within the OSF repository). These subjects had no access to the regulatory behaviors subjects actually used. This decontextualized manipulation of emotional experiences in scenarios unburdened by the complications of reality more closely mirrors the design of a stimulus–response paradigm while retaining content similar to the haunted house. If there is a difference between participants simulating (i.e., strategy forecasting) self-regulation and participants performing (i.e., strategy using) self-regulation, it may further emphasize the effects that complexity and lack of control introduce to the ER space. We report how we determined our sample

size, all data exclusions, all manipulations, and all measures in the study.

## Participants

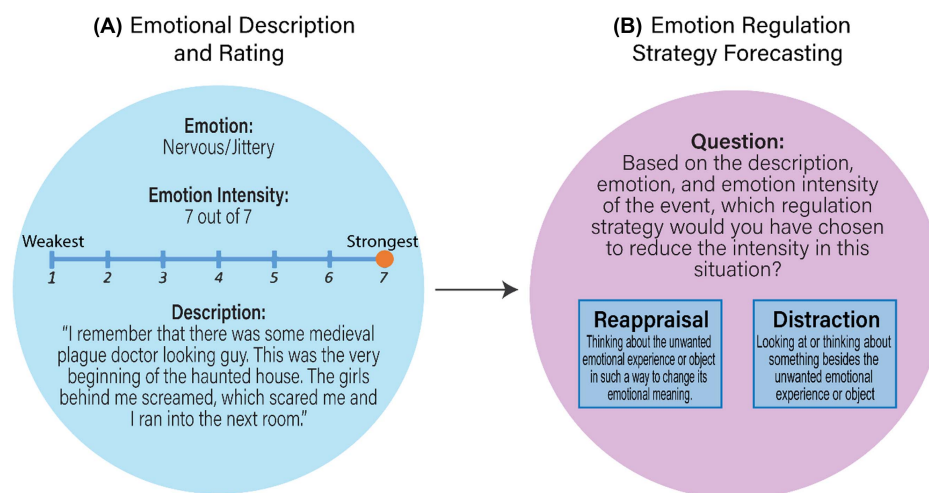
In July 2021, 170 participants (age:  $\bar{x}_{age} = 34.34$  years, range = 18–75 years,  $SD_{age} = 14.31$  years; gender: 100 female, 68 male, two nonbinary) consented to an IRB-approved online study described as measuring individual differences in choice predictions. Participants completed the study on Qualtrics and were recruited/filtered via Prolific. Eligible participants were native English speakers residing in the United States between the ages of 18 and 85, had normal or corrected-to-normal vision, had no history of reading-related disorders or literacy difficulties, as well as no history of mild cognitive impairment, head injury leading to unconsciousness, or unregulated mental health diagnosis. The racial identity of participants were as follows: 13.6% Asian, 06.8% Black, 04.3% mixed, 03.7% other, and 71.6% White. Although socioeconomic status data is not available, 45.2% of participants reported working full-time, 19.2% reported working part-time, 24.7% reported not working full- or part-time, and 11.0% did not specify their work status.

Sample size was determined via a priori power analyses assuming an attrition rate of 10%,  $r^2 \leq 0.10$  for covariates, and a small effect size ( $OR = 1.68$ ), which suggested we must recruit at least 163 participants to achieve  $1 - \beta = 0.80$  ( $\alpha = .05$ , two-tailed); however, this approach had not taken into account the hierarchical nature of our observations and likely underestimates our true power. Eighteen participants were excluded for failing attention checks ( $n = 7$ ), failing to complete the study ( $n = 9$ ), and scoring a Q Recaptcha Score lower than 0.7, indicating significant bot activity ( $n = 2$ ). Participants were paid at a rate of \$10.25/hr.

## Materials and Procedure

Details from 78 negatively valenced preliminary study events regulated through either reappraisal or distraction were presented to online participants. Participants first read definitions of both reappraisal (thinking about the experience in a way that reduces the intensity of the negative emotions) and distraction (looking or thinking about something else that is emotionally neutral) and reviewed examples of how both strategies might be employed. These haunted house-specific examples included the following: (a) making an effort to remind oneself that the people are just actors who are using props, rather than zombies trying to hurt them, and (b) choosing to look down at one's feet or focusing on what one ate for lunch rather than focusing on the zombies coming after you, for reappraisal and distraction specifically. Participants performed a brief practice task that required successfully defining and applying both categories before the primary task began (Figure 3). Participants were provided an opportunity to pause participation and contact research staff if they had questions about definitions or strategy application before proceeding. All 78 events were randomized and serially presented. These events were screened for information pertinent to reappraisal and distraction that may unduly influence participant decisions. For each event, the emotions experienced, the intensity of each emotion, how the original regulation strategy user described the event, and definitions for both strategies were displayed. Participants were then asked to predict which strategy they would choose to reduce the emotional intensity of the situation. Participants were granted as much time as needed to complete the task. Following the primary task, participants completed individual difference measures, including the ERQ, the Difficulties with Emotion Regulation Survey (DERS), and the IUS. Participants completed the study in 33.7 min on average ( $Mdn = 31.5$  min,  $SD = 14.2$  min, range = 10.9–88.4 min).

**Figure 3**  
Study 2 Task Overview



*Note.* One hundred seventy participants, or forecasters, (A) read the descriptions and emotion intensity ratings that preliminary study participants (experiencers) reported occurred while in the haunted house and then (B) indicated which regulation strategy (distraction or reappraisal) they predict they would use to regulate their emotions in the described event. See the online article for the color version of this figure.



## Analysis

To explore whether the affective intensity that strategy users reported influenced the strategies that strategy forecasters predicted, we again specified mixed effect binary logistic regressions accounting for the random effect of participant (both the strategy forecaster and strategy user of each observation) using the “lme4” package (Bates et al., 2015) in R (R Core Team, 2022) and followed an information theoretic approach via AIC comparison. Fixed effects models were built iteratively from and compared to our null model ( $ICC = 0.14$ ). All data and scripts used to produce this analysis are publicly available at the OSF (see [https://osf.io/j5sku/?view\\_only=89d87669e7674096819c439ca109c483](https://osf.io/j5sku/?view_only=89d87669e7674096819c439ca109c483)). The design and hypotheses of Study 2 were preregistered with AsPredicted ([https://aspredicted.org/XXH\\_W1V](https://aspredicted.org/XXH_W1V)), though please note a discrepancy exists in the number of events used, as fewer events met our outlined criteria than initially determined.

## Study 2: Results

### Study Samples Were Similar Across Individual Difference Measures

Our first analyses aimed to determine whether relevant trait differences existed between the sample of strategy forecasters and the sample of strategy users. If such differences exist, they would limit our ability to associate differences in regulatory forecasting or usage to differences in presentation and context. Both preliminary and Study 2 participants completed the ERQ and IUS. If differences exist in ERQ scores, the groups may differ in their underlying propensity to choose specific strategies. Using a Welch's two-sample  $t$  test, we did not find significant differences between the groups in their likelihood of using reappraisal,  $\bar{x}_{\text{users}} = 29.9$ ,  $\bar{x}_{\text{forecasters}} = 31.0$ , 95% CI  $[-3.22, 1.03]$ ,  $t(44.6) = -1.04$ ,  $p = .305$ , according to the ERQ reappraisal subscale. However, significant differences were observed between the two groups for the expressive suppression ERQ subscale,  $\bar{x}_{\text{users}} = 12.5$ ,  $\bar{x}_{\text{forecasters}} = 15.7$ , 95% CI  $[-5.03, -1.32]$ ,  $t(48.1) = -3.44$ ,  $p = .001$ . The relevancy of the suppression subscale is unclear in this context, as suppression is not directly tested, and neither subscale proved to be predictive of strategy usage during our preliminary study. Furthermore, a bivariate linear model found that neither the ERQ reappraisal subscale ( $b = -0.001$ ,  $SE = 0.002$ ,  $p = .58$ ) nor the suppression subscale ( $b = 0.002$ ,  $SE = 0.002$ ,  $p = .35$ ) predicted the proportion of trials in which participants selected reappraisal rather than distraction in this study as well. Additionally, if differences exist in IUS scores, the groups may differ in how they respond to ambiguity or uncertain situations, perhaps especially relevant given that “confused” was the most cited negative emotion in Study 1. However, no differences were observed in IUS scores across groups,  $\bar{x}_{\text{users}} = 33.6$ ,  $\bar{x}_{\text{forecasters}} = 34.3$ , 95% CI  $[-7.07, 5.59]$ ,  $t(34.9) = -0.238$ ,  $p = .813$ . Assessing differences in difficulties in applying emotion regulation strategies via DERS subscales was not possible because it was not administered to preliminary study participants.

### Intensity Predicts Regulatory Strategy Forecasts

Our first model—containing only the affective intensity of strategy users as a predictor to predict strategy forecasters' predictions—performed better than our null model,  $\chi^2(1, N = 25,232) = 8.39$ , demonstrating a small positive effect ( $OR = 1.06$ , 95% CI  $[1.02,$

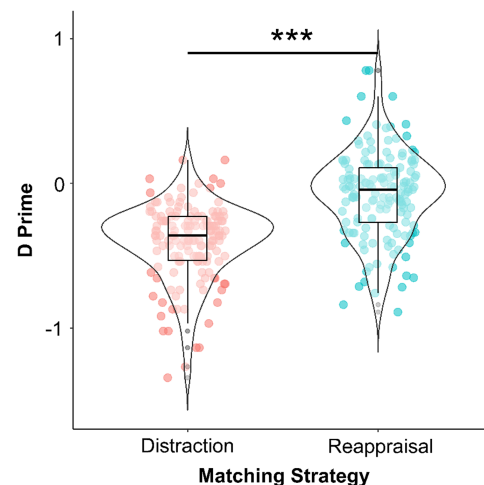
$1.10]$ ,  $p = .004$ ) such that more intense events were associated with an increased probability that participants predicted choosing distraction to regulate them. Additional models included age, gender, IUS score, the DERS limited access to strategies subscale, and a combination of all four as covariates. However, each model failed to outperform our initial model in chi-square tests of the models, age:  $\chi^2(1, N = 25,232) = 0.84$ ,  $p = .36$ ; gender:  $\chi^2(2, N = 25,232) = 2.81$ ,  $p = .25$ ; IUS:  $\chi^2(1, N = 25,232) = 1.25$ ,  $p = .26$ ; DERS:  $\chi^2(1, N = 25,232) = 0.54$ ,  $p = .46$ ; combo:  $\chi^2(5, N = 25,232) = 4.52$ ,  $p = .48$ ; respectively.

### Strategy Forecasters Matched Strategy Users Less Than Chance When Selecting Distraction

In signal detection theory,  $d'$  prime ( $d'$ ) is a measure of sensitivity that quantifies the ability to distinguish between signal and noise in a binary decision task and thus can be used to determine whether congruency in strategy between strategy forecasters and strategy users is greater than chance.  $d'$  is calculated as the normalized value of the proportion of hits (i.e., when a strategy was used by a strategy use participant and predicted by a strategy forecasting participant) minus the proportion of false alarms (i.e., when a strategy was not used by a strategy use participant but was predicted by strategy forecasting participant). Importantly,  $d'$  is robust to unequal prior probabilities in binary outcomes, as occurs in our strategy selection (73.1% of preliminary study observations used distraction) through the incorporation of a bias parameter. Using this approach, we found that strategy forecasting participants matched the experiences of strategy-using participants in their selection of reappraisal nearly at chance ( $d' = -0.08$ ) but were below chance in matching distraction ( $d' = -0.41$ ; Figure 4). The difference in selection congruency

**Figure 4**

*Forecasted Versus Experienced Regulation Usage*



*Note.* Participants' predicted strategies were compared to the strategies experienceders reported actually using in each situation. Although neither strategy was used more frequently than chance, participants were significantly more likely to predict they would use reappraisal in situations where they ultimately used distraction compared to predicting distraction in situations where they ultimately used reappraisal. See the online article for the color version of this figure.

\*\*\*  $p < .001$ .

between these strategies was significant as determined by a paired samples  $t$  test,  $\bar{x}_{\text{diff}} = 0.328$ , 95% CI [0.313, 0.342],  $t(149) = 43$ ,  $p < .001$ , suggesting that differences in the deployment of distraction between the two groups may be driving differences in how predictive affective intensity was toward strategy forecast or usage across these two contexts. The distribution of strategy selection differed between our strategy forecasting sample and strategy use sample, as distraction was only selected in 48.8% of observations for Study 2. Taken together, we found that participants used emotional intensity to inform their ER strategy predictions but not strategy usage and that the predicted utility, and thus frequency, of using distraction in such a context might not reflect what is experienced in practice.

### Study 3: Method

Though affective intensity failed to predict ER usage in a high-intensity, quasinaturlistic setting, participants presented with descriptions of events that were regulated by “strategy users” were more likely to forecast using distraction to regulate events described as high intensity and reappraisal for events described as being of a lower intensity. The different results observed in these studies are difficult to directly compare, though, as many features differ between the approaches. Participants in Study 1 experienced the haunted house, were not trained or prompted to self-regulate, experienced the emotions that they reported, and reported the regulatory strategies that they used. Participants in Study 2 simulated the experiences of the haunted house, were instructed in ER strategies and prompted to make a forecast, did not experience the emotions associated with the event, and reported what strategy that they forecasted they might use in the given situation. Furthermore, Study 1 did not attempt to manipulate the emotions of participants, instead prioritizing ecological validity by observing self-report after exposure. A study that keeps instruction and stimulus exposure constant while differing the type of regulation (i.e., strategy forecasting vs. usage) measured would be more conducive for direct comparisons of these two regulation processes. Study 3 attempted to rectify these discrepancies using a 2 Between (Condition: Forecast vs. Experience)  $\times$  2 Within (Intensity: Low vs. High) mixed study design. Because we could not incorporate an immersive experiential component such as in Study 1 in this experimental design,<sup>1</sup> we instead used clips from lesser known horror films to elicit regulatory response to feature-rich, dynamic representations of negative emotion. This design allows us to directly compare the differences in regulatory behavior among untrained and unprompted participants when either reporting actual usage or forecasted selection in response to high- and low-intensity stimuli.

We originally hypothesized that we would replicate the results of Study 1 and Study 2: that participants placed within the “strategy user” condition would not demonstrate a relationship between stimulus intensity and regulation strategy usage due to the added complications and design decisions that reduce experimental control relative to similar designs, while participants in the “strategy forecaster” condition would demonstrate the canonical relationship between stimulus intensity and regulation strategy usage (i.e., as affective intensity increases, the likelihood of relying upon distraction also increases). Counter to our predictions, we found that both conditions demonstrated characteristics of this canonical relationship; however, important differences in ER strategy and effectiveness were also observed across the two conditions. We

report how we determined our sample size, all data exclusions, all manipulations, and all measures in the study.

### Participants

In October 2023, 247 participants (age:  $\bar{x}_{\text{age}} = 38.57$  years, range = 20–76 years,  $SD_{\text{age}} = 12.24$  years; gender: 94 female, 152 male, one nonbinary) consented to an IRB-approved online study described as using clips from horror films to explore emotions and behavior. Participants completed the study on Pavlovian and were recruited/filtered via Prolific. Eligible participants were native English speakers residing in the United States between the ages of 18 and 85, had normal or corrected-to-normal vision, had no history of reading-related disorders or literacy difficulties, as well as no history of mild cognitive impairment, head injury leading to unconsciousness, or unregulated mental health diagnosis. The racial identity of participants was as follows: 08.9% Asian, 06.9% Black, 05.7% Hispanic, 09.3% mixed, 04.6% other, and 64.6% White. Socioeconomic status was well distributed, with 09.3% reporting a household income of under \$15,000 per year, 09.3% between \$15,001 and \$25,000, 10.5% between \$25,001 and \$35,000, 13.4% between \$35,001 and \$50,000, 19.0% between \$50,001 and \$75,000, 13.8% between \$75,001 and \$100,000, 08.1% between \$100,001 and \$150,000, 06.9% above \$150,000, and an additional 04.9% who did prefer not to say. In response to the question, “How much do you enjoy watching horror movies?” the average participant response was a 2.95 on a scale from 0 to 6, with 0 corresponding to “not at all” and 6 corresponding to “extremely” ( $Mdn = 3$ ,  $SD = 2.16$ ).

Sample size was determined via a priori power analyses assuming an attrition rate of 10%,  $r^2 \leq 0.10$  for covariates, and the most conservative effect size observed in our previous studies ( $OR = 1.30$ ). To achieve  $1 - \beta = 0.80$  ( $\alpha = .05$ , two-tailed), at least 240 participants were required, or 264 when accounting for attrition. Up to 300 slots were made available on Prolific to account for returned or incomplete research participation. Five participants were excluded for failing attention checks ( $n = 1$ ) and familiarity with the stimuli ( $n = 4$ ). Though we did not meet our recruitment goal of  $n = 264$ , our sample ( $n = 242$ ) still surpassed the threshold calculated to achieve sufficient power. Participants were paid at a rate of \$12.00/hr.

### Materials and Procedure

Participants completed a web browser-based task built primarily with jsPsych V7.0 (De Leeuw et al., 2023). Following consent and a disclaimer regarding the content of the stimuli (i.e., gore, violence, mature language, harm to self or others), participants were instructed to complete the study in an isolated, distraction-free space without others present to improve immersion. Participants were also instructed to set audio to a comfortable but audible level, to silence their phones, and to minimize or close other programs. To further standardize the experience and minimize distractions, the task was programmed to automatically run the browser in full-screen mode, and the task was programmed to stop if full-screen mode was exited. Mobile devices, tablets, and screens with a resolution of less than  $700 \times 1,250$  pixels were eligible to participate.

<sup>1</sup> The haunted house has a limited seasonal run time, and we cannot modify the intensity of the events in the haunted house as it is run by a private company.

Participants were instructed to watch and react to each of the four video clips as they naturally would. These instructions appeared as a reminder before each video played. Before each stimulus, participants were asked, “How intense are the negative emotions that you feel before starting this clip?” with responses captured on a linear sliding scale ranging in values from 0 (labeled “not at all intense”) to 100 (labeled “extremely intense”). Which side of the scale corresponded to which label was counterbalanced across participants. The default value of the slider thumb was set to 50, and participants were required to interact with the slider thumb before progressing. As participants moved the slider thumb, the value corresponding to its position was visualized and updated accordingly. Video order was randomized. After each video, participants were asked, “How intense were the negative emotions that you felt while watching this clip?” Responses were captured using the same scale as previously described. However, participants were also reminded of the value that they had selected prior to starting the video (e.g., a participant who indicated a 77 on the scale before watching the video saw the message: “Before this video, you reported your negative emotions were at: 77”).

All video clips were 120 s in length and pulled from relatively lesser known independent horror films, including *Vicious Fun* (Particular Crowd, Black Fawn Films), *The Marshes* (28 Productions), *Head Count* (Godmother Industries), and *Superhost* (Superchill). Forty hypothesis-blind independent raters watched and rated these clips, as well as six other films, on a scale from 0 to 100 across metrics including arousal, valence, narrative coherence, and familiarity. These four clips were chosen due to their low average familiarity values (range  $\bar{x} = 0.25\text{--}6.05$ )—indicating that few participants would have likely seen them before—and negative median valence scores (i.e., values below 50;  $\bar{x}_{\text{Vicious Fun}} = 15$ ,  $\bar{x}_{\text{The Marshes}} = 01.5$ ,  $\bar{x}_{\text{Head Count}} = 33.5$ ,  $\bar{x}_{\text{Superhost}} = 25.5$ ). They were also chosen for having either relatively high or relatively low median arousal scores ( $\bar{x}_{\text{Vicious Fun}} = 77.5$ ,  $\bar{x}_{\text{The Marshes}} = 70$ ,  $\bar{x}_{\text{Head Count}} = 50.7$ ,  $\bar{x}_{\text{Superhost}} = 58.5$ ) and minimal variance around those values. This allowed us to attempt to manipulate the affective experiences of participants to influence self-regulation behaviors.

After viewing and rating all videos, Study 3 participants were assigned to either a “strategy use” ( $n = 130$ ) or “strategy forecast” ( $n = 112$ ) condition. Both conditions were given descriptions and examples of distraction and reappraisal that mirrored those used in Study 2 (though “haunted house” was replaced with “horror movie”). Whether participants received the description and examples of distraction or reappraisal first was counterbalanced across participants. However, following these descriptions, participants were asked, “Which strategy, if any, did you use to regulate your negative emotions while watching this clip?” (strategy use condition) or “Which strategy, if any, would you predict the average person would use to regulate their negative emotions while watching this clip?” (strategy forecast condition). Participants responded to this question by selecting either “reappraisal,” “distraction,” or “neither.” The order in which these options appeared was randomized for each participant. Reminders of what the three options referred to appeared below these options. Reminders for participants in the strategy use condition read, “CHOOSE REAPPRAISAL if you changed how you thought about the video; CHOOSE DISTRACTION if you diverted your attention from the video; CHOOSE NEITHER if you did not implement either of the other two strategies.” Reminders for participants in the strategy forecast condition read, “CHOOSE REAPPRAISAL if they

should change how they thought about the video; CHOOSE DISTRACTION if they should divert their attention from the video; CHOOSE NEITHER if they should not implement either of the other two strategies.” Note that a potential discrepancy exists between the phrasing of our strategy forecast instructions (“Which strategy ... would you predict”) and reminders (“if they should”), which we discuss further in the limitations. If participants selected neither, they were not asked any further questions for that stimulus. If participants selected a nonneither option, they were asked how much the strategy they used reduced or the strategy they forecasted would reduce negative emotions while watching the stimulus on a 0–100 scale as previously described. Participants also either answered how effortful it was to use a strategy and how successfully they could use it or how effortful they predicted it might be and how successfully they predicted it could be used. These were each captured on 7-point Likert scales. Labels included “not at all,” “slightly,” “somewhat,” “moderately,” “considerably,” “very much,” and “extremely.” Participants responded to questions for each clip in the order that they clips were watched and a still from each clip was centrally placed on the screen for each question to ensure participants understood which stimulus that they question was referring to. Following all questions, participants were asked to provide a brief example of both reappraisal and distraction in a free-response textbox to further assess task comprehension. Following the primary task, participants completed individual difference measures, including the ERQ, the DERS, and the IUS. Participants completed the study in 21.9 min on average ( $Mdn = 20.5$  min,  $SD = 56.0$  min, range = 13.6–50.7 min). For additional information, see our OSF repository containing all task materials, including instructions and texts (see [https://osf.io/j5sku/?view\\_only=89d87669e7674096819c439ca109c483](https://osf.io/j5sku/?view_only=89d87669e7674096819c439ca109c483)).

## Analysis

To explore whether affective intensity and condition influenced the strategies participants used or predicted, we again specified mixed effect binary logistic regressions accounting for the random effect of participant and stimulus using the “lme4” package (Bates et al., 2015) in R (R Core Team, 2022) and followed an information theoretic approach via AIC comparison. Fixed effects models were iteratively built from and compared to our null model ( $ICC = 0.162$ ), which did not contain any fixed effects. All data and scripts used to produce this analysis are publicly available at the OSF (see [https://osf.io/j5sku/?view\\_only=89d87669e7674096819c439ca109c483](https://osf.io/j5sku/?view_only=89d87669e7674096819c439ca109c483)). The design and hypotheses of Study 3 were preregistered with AsPredicted (<https://aspredicted.org/n3ne3.pdf>).

## Study 3: Results

### Video Stimuli Elicited Predictable Emotional Responses

To ensure that our emotion manipulation was successful, negative affective intensity ratings following each low- and high-intensity stimuli were compared using Welch’s two-sample  $t$  test, which found that our manipulation was successful,  $\bar{x}_{\text{high}} = 53.5$ ,  $\bar{x}_{\text{low}} = 40.6$ , 95% CI [9.1, 16.8],  $t(948.1) = 6.61$ ,  $p < .001$ . The average baseline intensity (i.e., intensity assessed prior to each video) was 27.4 pts ( $Mdn = 19$ ,  $SD = 27.0$ ) while the average postexposure intensity was 47.1 pts ( $Mdn = 50$ ,  $SD = 30.9$ ).



### Strategy Forecasters and Users Reported No Differences in Emotional Intensity

Though participants were randomly assigned to conditions after having provided affective ratings, we wanted to ensure that any effects discovered between conditions could not be attributable to differences in experienced affective intensity. A Welch's two-sample *t* test comparing affective intensity ratings between strategy users and forecasters both before,  $\bar{x}_{\text{user}} = 26.2$ ,  $\bar{x}_{\text{forecaster}} = 28.8$ , 95% CI [-6.1, 0.8],  $t(908.3) = -1.50$ ,  $p = .134$ , and after  $\bar{x}_{\text{user}} = 46.5$ ,  $\bar{x}_{\text{forecaster}} = 48.0$ , 95% CI [-5.4, 2.4],  $t(917.9) = -0.73$ ,  $p = .460$ , stimulus exposure found no statistically significant differences in affective ratings. Strategy forecasters and users also did not differ across any relevant individual difference measures or demographics, including the reappraisal,  $t(198.6) = 0.14$ ,  $p = .890$ , and suppression,  $t(222.57) = -1.94$ ,  $p = .054$ , ERQ subscales; both Factor 1,  $t(235.0) = -0.94$ ,  $p = .349$ ; and Factor 2,  $t(220.4) = -0.96$ ,  $p = .336$ , of the IUS scale; the limited access to strategies subscale of the DERS,  $t(221.4) = 0.08$ ,  $p = .938$ ; age,  $t(220.0) = -0.14$ ,  $p = .888$ ; or horror enjoyment,  $t(225.9) = 0.12$ ,  $p = .908$ .

### Intense Emotional Responses Were More Likely to Be Regulated

To add greater ecological validity to a forced-choice paradigm, we provided participants the option to indicate whether a stimulus should be regulated (i.e., reappraisal or distraction) or not regulated (i.e., neither). In line with hedonic motivations to self-regulate, we expect that videos of greater self-reported negative affective intensity should be more likely to be regulated; if that is not the case, then our design may generate noisy or counterintuitive results. To that end, we did find that videos in which participants selected neither distraction nor reappraisal were of a lower intensity,  $\bar{x}_{\text{regulated}} = 53.3$ ,  $\bar{x}_{\text{unregulated}} = 36.7$ , 95% CI [12.7, 20.],  $t(735.6) = 8.30$ ,  $p < .001$ , and a mixed effect binary logistic regression found that each standard deviation unit increase in affective intensity results in a 2.86-fold increase in the odds of self-regulation occurring (95% CI [2.16, 3.78],  $p < .001$ ).

### Strategy Forecasters Anticipated Regulating More Often Than Strategy Users; Strategy Users Reappraised More Often Than Strategy Forecasters

Overall, reappraisal was used or forecasted in 33.1% of trials, distraction was used or forecasted in 28.5% of trials, and 36.7% of trials were left unregulated or without either option being forecasted. To assess whether there were differences in the distribution of strategy usage or forecast by condition, which could have implications for our primary analysis, we conducted chi-square test on strategy use/forecast and condition, which found differences in the frequencies with which strategy forecasters and users left trials unregulated,  $\chi^2(1, N = 953) = 120.35$ ,  $p < .001$ , and used or forecasted a regulation strategy,  $\chi^2(1, N = 613) = 6.14$ ,  $p = .013$ . More precisely, strategy users reported regulating (52.6%) and not regulating (47.4%) about equally while forecasters heavily favored regulating (82.2%) over not regulating (17.7%) across trials (Figure 5A). Additionally, strategy users reported using reappraisal (59.8%) more often than distraction (40.2%) while strategy forecasters predicted choosing both distraction (49.2%) and reappraisal (50.7%) about evenly (Figure 5B).

### Strategy Forecasters and Users Differ in Strategy Selection Probability at Low, Not High, Intensities

Following the analysis plan outlined within the Study 3 methods sections, we compared models via chi-square tests that included fixed effects for postexposure affective intensity, baseline affective intensity, condition, and an interaction between postexposure affective intensity and condition. These models were built iteratively, adding one effect at a time. Our best-fitting model included all four terms,  $\chi^2(1, N = 597) = 4.205$ ,  $p = .040$ , and found the interaction was predictive of strategy usage/forecasting ( $OR = 0.56$ , 95% CI [0.36, 0.87],  $p = .010$ ). Having tested the model that we hypothesized, we identified a selection of possible covariates (age, horror, enjoyment, ERQ subscales, IUS subscales, and the DERS limited access to strategies subscale) and iteratively added them to the model in order of most correlated with the outcome variable to pursue the model of best fit. Only the addition of the reappraisal ERQ subscale improved model fit above that of our hypothesized model,  $\chi^2(1, N = 597) = 9.3587$ ,  $p = .002$ . This model yielded a significant interaction term ( $OR = 0.61$ , 95% CI [0.39, 0.95],  $p = .029$ ) and suggests that condition is moderating the relationship between affective intensity and strategy usage/forecasting. More specifically, at high intensities, both strategy forecasters and users are similar in their likelihood of predicting or using distraction, respectively. However, in congruence with forecasters predicting to choose reappraisal less than strategy users used it in practice, strategy forecasters are less likely to predict choosing reappraisal than strategy users were to use reappraisal at lower intensities (Figure 5C).

### Strategy Forecasters and Users Differ in Regulation Effort

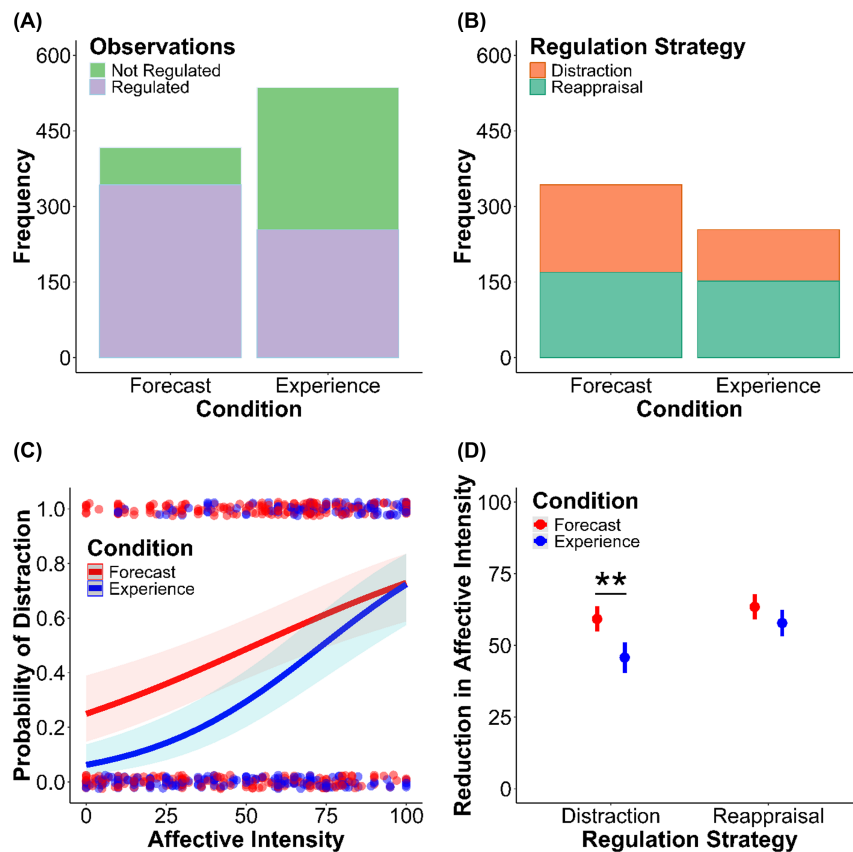
Participants in both conditions failed to generate significant differences in how much effort they exerted or predicted that they would exert to use reappraisal and distraction,  $F(1, 215) = 0.392$ ,  $p = .532$ . However, the participants in the use condition did differ from participants in the forecasting condition in how effortful regulation was across strategies, even when adjusting for strategy usage/forecast,  $F(1, 215) = 3.820$ ,  $p = .045$ . Bonferroni-adjusted post hoc contrasts determined that this difference is primarily driven by reappraisal; experiencers reported that reappraisal was more effortful than forecasted predicted it would be,  $\bar{x}_{\text{user}} = 3.11$ ,  $\bar{x}_{\text{forecaster}} = 2.60$ , 95% CI [0.13, 0.88],  $t(296.5) = .66$ ,  $p = .016$ .

### Strategy Forecasters and Users Differ in Regulation Intensity Reduction

When examining how effective participants thought the strategies would be at reducing affective intensity, adjusting for the random effect of participant, we found a significant main effect of strategy,  $\bar{x}_{\text{reappraisal}} = 61.9$ ,  $\bar{x}_{\text{distraction}} = 54.5$ , 95% CI [3.31, 11.48],  $t(582.12) = 3.55$ ,  $p < .001$ , and condition,  $\bar{x}_{\text{users}} = 55.0$ ,  $\bar{x}_{\text{forecasters}} = 61.1$ , 95% CI [-10.32, -1.85],  $t(494.6) = -2.83$ ,  $p = .004$ , but more intriguingly, in an interaction model we found a significant interaction between the two variables,  $F(1, 377) = 4.31$ ,  $p = .038$ . A subsequent Bonferroni-adjusted contrast revealed a significant difference between strategy users and forecasters in how effectively distraction reduces affective intensity,  $\bar{x}_{\text{users}} = 48.0$ ,  $\bar{x}_{\text{forecasters}} = 58.3$ , 95% CI [-16.62, -4.13],



**Figure 5**  
*Predicted Versus Experienced Regulation, Strategies, and Outcomes*



*Note.* (A) Chi-square tests indicate that participants who used a regulation strategy were more likely not to regulate a stimulus compared to those who only forecasted their strategy use. (B) Strategy forecasters predicted a more balanced use of reappraisal and distraction than what was observed in actual strategy usage. (C) Mixed-effects binary logistic regression revealed that affective intensity predicts strategy choice for both forecasters and actual users. At lower intensities, forecasters were less likely to predict using reappraisal than actual strategy users were to select it. (D) Forecasters anticipated that distraction would reduce negative affective intensity to a greater extent than strategy users reported experiencing. Error bars represent 95% confidence intervals. See the online article for the color version of this figure.

\*\*  $p < .01$ .

$t(198.2) = -3.28, p = .001$  (Figure 5D). This finding is congruent with findings from both Study 1 and Study 2 in which individuals seem to overestimate or miscalculate the effectiveness of distraction but not reappraisal within these settings.

### Transparency and Openness Practices

The preregistration for Studies 1, 2, and 3 can be found at [https://aspredicted.org/DP1\\_453](https://aspredicted.org/DP1_453), [https://aspredicted.org/XXH\\_W1V](https://aspredicted.org/XXH_W1V), and <https://aspredicted.org/n3ne3.pdf>, respectively. Deidentified data, analysis and data cleaning scripts, questionnaires, and data collection files to replicate the findings have been made publicly available via the Open Science Framework (OSF) and can be accessed at [https://osf.io/j5sku/?view\\_only=89d87669e7674096819c439ca109c483](https://osf.io/j5sku/?view_only=89d87669e7674096819c439ca109c483). All products generated from these data, including PowerPoints and posters highlighted under the author's note, have been made

available within this repository as well. The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

### General Discussion

Three studies examined the association between emotional intensity and regulation strategy usage in response to dynamic, multimodal stimuli of varying intensity. Study 1 tasked untrained participants with recalling emotional and spontaneous regulatory behaviors in a surprise recall task after exposure to a high-intensity multimodal context (a haunted house). Affective intensity did not predict strategy usage. Though distraction was used more often than reappraisal, distraction was less successful at regulating in response to high affective intensities in this context. Study 2 found an association between affective intensity and strategy usage among

participants forecasting regulatory behavior in response to descriptions of regulated events that haunted house participants actually experienced. However, strategy forecasters overpredicted how often distraction was used by participants who regulated within the haunted house (i.e., strategy users). Study 3 measured differences between strategy users and forecasters regarding ER within the same study and found significant differences between strategy forecasters and users in how often distraction was forecasted or used and how effective the groups predicted or reported distraction to be, respectively. The present findings highlight challenges in translating ER theory to real-world application, as uncontrolled, complex, and dynamic situations in everyday life may strongly influence the efficacy and frequency with which regulatory strategies are used.

These results add nuance to our understanding of affective intensity's influence upon regulation strategy application and complement research on environmental affordances, or the extent to which features of a situation lend themselves to either distraction or reappraisal (Suri et al., 2018; Young & Suri, 2020). It is possible that individuals initially regulated their emotions with the strategy they believed had the greatest value (i.e., the most effective strategy with the lowest effort investment; typically distraction) based upon models of regulation they had previously generated from experiences with similar media, as outlined by computational decision-making frameworks of ER (Etkin et al., 2015). The infrequent use of reappraisal relative to distraction mirrors findings from studies that suggest some less-costly strategies might act as "defaults" and interfere with the frequency of use of high-cost strategies like reappraisal (Suri et al., 2015). However, the unrelenting, attention-grabbing nature of challenging high-intensity situations may also grant few affordances by which to distract oneself, thus making distraction more costly in some circumstances. On the other hand, reappraisals may appear to be less valuable initially, resulting in lower usage, but could be more effective when used due to a relatively greater volume of environmental affordances (i.e., things to repurpose or reconstrue; Uusberg et al., 2019; e.g., actors, props, goals). This explanation mirrors the strategy-selection relationship hypothesized by Etkin et al. (2015), who posited that a more explicit, higher cost, model-based approach to ER may be applied more effectively when implicit, or model-free, ER tendencies were not arriving at their desired goal via prediction error adjustment alone. Distilling events down to a text-based representation or video, as had been done in Studies 2 and 3, may provide greater distraction affordances and rebalance the likelihood of individuals choosing or predicting reappraisal or distraction in situations when it would canonically make sense to do so.

How a person passively assesses the emotionally relevant features of an environment may guide regulatory behaviors, but so too might the action affordances—opportunities to move, modify, or engage with the environment—that a situation presents. Action-oriented perspectives on ER emphasize that emotion regulation behaviors are a product of active processes, such as forward modeling (Bramson et al., 2023). Common associations between self-regulation, emotion, and activity in the sensorimotor and premotor systems illustrate how entangled action is with regulation (Bramson et al., 2018; Mobbs et al., 2007; Saarimäki et al., 2016). The degree to which one is free to physically navigate their space or interact with evocative stimuli may have important implications on situational appraisals, thus informing which strategies participants predict may or may not work (Ridderinkhof, 2017). Figure 3 highlights one example of this within the haunted house, as a participant was able to mitigate a negative

emotional reaction by physically circumventing the stimulus. Stimulus-response paradigms that situate participants in stationary positions or lack contexts enveloping the emotionally evocative stimulus may not be well suited for modeling the effect that these factors have upon typical or daily ER strategy usage.

Hot-cold empathy gap research, which measures forecasting differences between how people think they will feel hypothetically and how they feel in practice (Loewenstein, 1996), is relevant as well. Individuals in "cold states" consistently underpredict the challenges associated with meeting affectively relevant goals during "hot states" (Sayette et al., 2008; Van Boven & Loewenstein, 2003). Such a pattern mirrors the differences observed between Studies 1 and 2, wherein decontextualizing events (i.e., shifting from a hot state to a cold state) yielded a predictable pattern in strategy choice not observed during hot state ER usage. They also mirror differences in strategy usage and success. Such patterns highlight that emotion self-regulation is a complex, multifaceted construct, and different proportions of its variability may be better captured by different approaches (Friedman & Gustavson, 2022). Though this study is the first to our knowledge that has utilized a high-intensity, dynamic, feature-rich paradigm to demonstrate this in the domain of ER, similar approaches have demonstrated similar discrepancies in the moral domain (FeldmanHall et al., 2012). Computerized lab tasks have been theorized to assess regulatory performance in optimal conditions (Wennerhold & Friese, 2020), and this may contrast study designs such as Study 1, which may be closer to performance in typical conditions, and Studies 2 and 3, which may be somewhere inbetween (Friedman & Gustavson, 2022). Though participants may be capable of performing self-regulation at high levels in optimal conditions, they may not feel motivated to do so in typical conditions (Grund & Carstens, 2019).

## Limitations and Future Directions

There are several limitations in our experimental approach that demand attention. First, our Study 1 aims were relatively narrow in comparison to the vast ER behavior variability captured by this data set and resulted in excluding many observations that did not meet our inclusion criteria (see Figure 1B). More analyses would be required to fully explore this space. Additionally, though many features of our design mirror regulation of emotions in everyday life, haunted houses may have limited generalizability to other high-intensity settings that we commonly experience (Clasen et al., 2019; Tashjian et al., 2022), and the purpose haunted houses commonly serve (i.e., entertainment) could also circumscribe their generalizability to graver situations. The use of a haunted house as our setting also may have resulted in self-selection biases within our sample. It must be noted that we did not directly manipulate emotional intensity within this design, and most of the self-report data that we did collect were captured postexposure, not during exposure. Thus, without manipulation, it is unclear whether self-reported emotion intensity in Study 1 represents a precursor to regulation, a product of regulation, or some combination of the two. Although computing standardized emotion scores of each event within the haunted house would be ideal and theoretically possible, the limited window in which we had to collect our experimental data made it difficult to assemble an additional independent sample for this purpose. While we chose language that aimed to target emotion as a precursor, it is entirely possible that subjects may have misremembered or

misinterpreted this intent. While some of our exploratory analyses suggest that the relationship between intensity and self-regulation failed to materialize even with stimulus manipulation (i.e., using section as a predictor of regulation) and an aggregate of negative emotion intensity (i.e., using a leave-one-out approach as a predictor of regulation), these analyses were limited due to low resolution and the possibility of low power, respectively. Because of this design, the results of Study 1 analyses are not conclusive. Additionally, we unfortunately did not have measures of startle sensitivity or fear enjoyment from Study 2 participants. Thus, we cannot compare our Study 1 and Study 2 samples along these metrics, which explain some of the differences in regulatory behaviors between samples. Studies 2 and 3 were also conducted entirely online. Though means of standardizing the experience were attempted, we have less control than possible in an in-person context and cannot guarantee that participants were fully focused on study tasks. Additionally, the choice to homogenize stimuli for strategy forecasters and users in Study 3 may have also unintentionally homogenized the regulation processes that we intended to target. In other words, forecasters may have just been tempted to report the strategies that they used, and users may have been tempted to report what they *would* have used had they regulated. However, the inclusion of a “no regulation” option was intended to reduce the latter possibility.

Participants in Study 3 were initially instructed to predict what strategy they believed the average person *would* choose while the strategy reminders phrased strategy selection as what average persons *should* choose. Both phrasings do imply some form of forecasting, but the former may be more likely to elicit *descriptive* forecasts and the latter more likely to elicit *prescriptive* forecasts, and these may lead to different regulatory conclusions. For example, a person might know that they *should* reduce stress by seeking therapy but might instead engage in maladaptive methods of stress reduction, such as substance abuse. Choice normativity (i.e., variance around which action one *should* take) is well-studied in health, moral, and social psychology but has been comparatively unexplored in emotion regulation. Extant ER literature highlights variance around how people regulate, but not necessarily around how they think they should regulate or how they think they would regulate. Regardless, this inconsistency may have introduced confusion into participant forecasting, and the extent to which this may have had impacts upon the outcome of Study 3 is unknown.

A small but important contingent of the existing ER literature has highlighted intrastrategy heterogeneity in the regulation techniques that we had examined (Uusberg et al., 2019; Webb et al., 2012). For example, Webb and colleagues identified at least three distinct ER approaches that could be categorized as reappraisal (i.e., reappraising the stimulus, reappraising the emotional response, reappraisal via perspective taking), and these reappraisal subtypes demonstrate varying effectiveness in modulating emotion depending upon situational and personal factors. It may be the case that specific types of reappraisal and distraction demonstrate an intensity-selection relationship that better mirrors the canonical association observed in lab studies, but testing such a question with sufficient power would necessitate far more observations than are available in this data set.

Due to resource constraints, participants also necessarily experienced the haunted house in groups. Although participants were instructed to not discuss their experiences and post hoc analyses failed to find any association between group membership and strategy usage, the group context in which the experience occurred could have

influenced behavior and cognitive perceptions in unknown ways. The presence and strength of friendship among group members was also assessed and was not predictive of regulation. Last, some events, particularly in the preliminary study and multiverse analyses, had to be captured at a 1-week delay due to collaboration with a memory study, which calls into question the reliability of some responses. Future research should limit the delay between experience and report as much as possible without interfering with emotional events. Future research might also take interest in the order of strategies reported in regulation-challenging situations; that is to say, does the likelihood of using a reappraisal strategy for a given person in this context increase with each failed attempt to engage distraction? Although we did not have sufficient observations to examine the data with such granularity, examining associations between the intensity of specific emotions and regulation usage might also be of particular interest to future researchers in this space (Young & Suri, 2020). Despite its limitations, this data set and approach may be of interest to those exploring spontaneous regulation tendencies from untrained participants in response to both positive and negative events.

## Conclusion

Taken together, the present studies represent what we believe to be the first attempt to extend the association observed between affective intensity and different ER behaviors to dynamic, multimodal, and high-intensity settings using untrained participants. This approach offers an alternative means of exploring ER usage while pursuing greater ecologically valid in study design. Our data and results may be of particular interest to other emotion, self-regulation, and cognitive control researchers interested in quasinaturalistic design. In failing to replicate lab results with Study 1 but finding a modest association in Studies 2 and 3, we may offer greater support for the importance of context in determining the fit of ER strategies, though the limitations inherent to this study leave room for other possibilities. Ultimately, though, this study highlights the importance of extending what we know about regulation in relatively mundane, controlled situations to those crowded, loud, and perhaps uncontrollable contexts in which emotion regulation success could be of dire consequence.

## Constraints on Generality

We aimed to generalize our findings to the downregulation of negative emotions by nonclinical U.S. populations in high-intensity, dynamic, and/or multimodal emotional situations. However, the setting of Study 1 (i.e., a haunted house) likely will not generalize to all dynamic, multimodal emotional situations. Studies 2 and 3 contain reasonably representative samples in terms of education, socioeconomic status, and race but were collected online, thus limiting generalizability to nonoptimal settings. Our recruitment added additional constraints as well. Using horror-related stimuli likely resulted in a self-selection bias. Participants in Study 1 skewed young, falling between the ages of 18 and 34, and were recruited from an urban setting, which may limit the applicability of our conclusions to children, older age groups, or individuals living in nonurban settings. Participants skewed more female than male in Studies 1 and 2 and more male than female in Study 3, which may result in an underrepresentation of men and women, respectively. Last, racial demographic information was not captured in Study 1, which leaves questions of racial representation unanswered. Future

research should explore these phenomena in other novel settings with a wider age range and balanced gender ratio to enhance the external validity of our findings.

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