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Coping through Precise Labeling of Emotions: A Deep Learning Approach to Studying
Emotional Granularity in Consumer Reviews

ALI FARAJI-RAD

ALI TAMADDONI

ATEFEH JEBELI

AUTHOR NOTE

Ali Faraji-Rad is Assistant Professor of Marketing at the Smith School of Business, University of Maryland, College Park. Ali Tamaddoni is Associate Professor of Marketing at Deakin Business School, Deakin University, Australia. Atefeh Jebeli is a PhD student in Information Systems, University of Maryland, Baltimore County. The authors have no conflict of interest to disclose. The authors thank Dr. Joseph Reiff and Dr. Katie Hoemann for their feedback on this research. The authors also thank Dr. Katie Hoemann for sharing the data for pilot study 1. Correspondence concerning this manuscript should be addressed to Ali Faraji-Rad (afr@umd.edu).

CONSUMER RELEVANCE AND CONTRIBUTION STATEMENT

Three decades of research in psychology have shown that people's ability to describe their negative emotions granularly is correlated with successful coping. We introduce the concept of emotional granularity to the consumer behavior literature and develop a novel deep-learning-based method to measure the extent to which consumers describe their emotions granularity via their language. While earlier methods of measuring emotional granularity primarily measure it at the trait level using self-reporting or experience sampling, our method unobtrusively measures the construct at the situation-specific level, using textual data generated by consumers. Thus, our method may be used more effectively to study the role of emotional granularity in consumer decision making. We study how granularity in describing negative emotions, as a predictor of coping success, predicts online reviewers' rating of service providers after negative experiences. We demonstrate several novel effects: 1) especially when the overall experience with the service provider is negative, greater emotional granularity in describing negative emotions in reviews is associated with more positive ratings of the business; 2) as reviewers write more reviews, they describe their negative emotions more granularly, which predicts higher ratings for negative service experiences from reviewers with a more extensive history of writing reviews; 3) when the service experience is negative, the temporal distance between the negative consumption experience and the posting of the review is associated with a more positive rating of the business, and this effect is mediated by greater granularity in describing negative emotions as a predictor of coping success. Our results have implications for a) understanding the role of emotional granularity in consumer decision making; b) understanding the predictors of online review ratings, as an important category of consumer decisions; and c) profiling consumers based on psychological traits inferred from the online content they generate.

ABSTRACT (200/200)

When describing their emotions, people may demonstrate *emotional expertise* by differentiating between emotions when using emotional labels or use emotion labels interchangeably to indicate a general valence. The authors develop a novel deep-learning-based method to measure the granularity with which people describe their emotions via language. They investigate the role of emotional granularity in consumer decision making, specifically in relation to coping with negative consumption experiences described in online reviews. Granularity in describing negative emotions is associated with more successful coping with negative experiences. Therefore, especially when the overall experience is negative, in which case coping is most relevant, greater granularity in describing *negative* emotions predicts more *positive* ratings of the business. Furthermore, in line with the view that the ability to granularly describe negative emotions is a skill, reviewers progressively become more granular when describing their negative emotions as they write more reviews. Consequently, reviewers progressively provide more positive ratings for negative experiences as they write more reviews. Finally, a greater temporal distance between the consumption experience and the writing of the review predicts greater granularity in describing negative emotions. Consequently, when the overall experience is negative and coping is relevant, a greater temporal distance predicts more positive ratings.

Keywords: emotional granularity, coping, consumer experience, emotional expertise, online reviews, Large Language Models (LLMs)

INTRODUCTION

Consumers often use a variety of emotion labels (e.g., angry, frustrated, stressed, etc.) to describe how they feel as a result of consumption experiences. Research in psychology over the past three decades has shown that people differ in the degree of granularity with which they describe their emotions (e.g., Barrett et al. 2001; Barrett 2004; Erbas et al. 2018; Kashdan, Barrett, and McKnight 2015). Often viewed as an ability or skill (i.e., expertise in emotion; Hoemann et al. 2021), *emotional granularity* describes individuals' ability to represent their emotional experience in a nuanced and specific manner, often marked through language (Lee, Lindquist, and Nam 2017). A substantial stream of empirical research shows that granularity in *negative* emotions predicts successful coping with these emotions (Barrett et al. 2001; Kashdan et al. 2010; Starr et al. 2019; Tomko et al. 2015). Despite the documented significance of emotional granularity in predicting people's decisions and behaviors (e.g., binge drinking, aggression, etc.; Kashdan et al. 2010), to date, the role of emotional granularity in consumer decision making has not been investigated.

In this research, we investigate the role of granularity in negative emotions in consumer decision making, following unpleasant service experiences, in the context of online reviews. As an empirical setting, online reviews include an overall rating, which is a holistic judgment about the company, as well as textual descriptions of the consumer experience. These textual descriptions provide valuable insights into the psychological processes that led to the holistic judgement. Furthermore, a consumer's decision about the rating to assign to a business after a service experience is extremely important to the business' success (Chevalier and Mayzlin 2006; Floyd et al. 2014; Proserpio and Zervas 2017; Vana and Lambrecht 2021; Varga and

Albuquerque 2023; Wu et al. 2015). Thus, we seek to provide more insight on what shapes this managerially important type of consumer decision.

Methods developed to measure emotional granularity in extant research primarily measure the construct at the trait level (i.e., individual differences in ability) (Hoemann, Barrett, and Quigley 2021). However, the construct may also be conceptualized at the situation-level (Barrett and Gross 2001), which is more relevant for studying it in the context of consumer experience. We utilize the BERT Large Language Model (Devlin, Chang, Lee, and Toutanova 2018) to develop a novel deep-learning-based method that enables us to determine the granularity with which consumers describe their emotions in online reviews. We then conduct a broad investigation of how granularity in negative emotions impacts consumers' rating of businesses, how reviewers' ability to granularly describe their negative emotions progresses as they write more reviews, and how the temporal distance between the consumption experience and the writing of the review, as a situational factor, predicts reviewers' granularity when describing their negative emotions, and ultimately impacts the rating assigned to the business.

We present several novel propositions by building on previous research which has shown that granularity in negative emotions is associated with more successful coping (e.g., Barrett et al. 2001). First, we propose that, particularly when the overall service experience is negative (i.e., when coping is most relevant), greater granularity in describing negative emotions is associated with more positive ratings of the business. This proposition stems from the fact that consumers who have already coped successfully with the negative experience are less likely to provide a negative holistic judgment of the business (i.e., 'penalize' the business). Second, consistent with the predominant view in the literature that the ability to differentiate between negative emotions is a skill (Hoemann et al. 2021), we propose that online reviewers will

progressively become more granular in describing their negative emotions as they write more reviews, which consequently predicts that as reviewers write more reviews, they provide more positive ratings for negative service experiences. Finally, we propose that a greater temporal distance between a negative consumption experience and the writing of a review increases reviewers' granularity in describing their negative emotions, which then contributes to more positive ratings of negative service experiences as temporal distance increases.

Our research primarily contributes to the stream of research on the role of context specificity of emotions in consumer decision making (e.g., Cavanaugh, Bettman, Luce 2015; Allard and White 2015; Raghunathan and Pham 1999), the factors that influence consumer review ratings (Aerts, Smits, and Verlegh 2017; Huang, Burtch, Hong, and Polman 2016; Schoenmueller, Netzer, and Stahl 2020), and the psychology of consumer language (e.g., Berger et al. 2019; Boghrati and Berger 2023; Packard and Berger 2023).

In the following, we present the theoretical background of our research, followed by an explanation of the method we have developed to measure emotional granularity in language use. We then present two pilot studies that validate our method. Then, in two studies, we analyze two large online review datasets of over 12 million reviews to test our hypotheses. Finally, we discuss the contributions and implications of our research for theory and practice, including its possible downstream implications for the psychological targeting of consumers (e.g., Matz and Netzer 2017).

CONCEPTUAL BACKGROUND

Emotional Granularity

A large body of research in psychology over the past three decades has shown that while some people are skilled at using differentiated and discrete emotion categories (e.g., agitated, angry, sad) to describe their emotions, others are not so skilled. This latter group instead communicates the general valence of how they feel by interchangeably using similarly valenced emotion labels (e.g., Barrett et al. 2001; Barrett 2004; Erbas et al. 2018; Kashdan, Barrett, and McKnight 2015). Psychological interest in emotional granularity stems largely from a broader interest in understanding people's competencies in recognizing and using their emotions (e.g., Barrett 2004; Hoemann et al. 2021; Quoidbach et al. 2014). It is suggested that during an emotion-evoking experience, people use all their relevant contextual knowledge to categorize the experience as a specific emotion (Barrett 2006). As Barrett et al. (2001) suggest, this knowledge may include information about the causes of the events (e.g., "angry *with* someone," "sad *about* something," "afraid *of* something"), the relational and cultural context of events (Mesquita and Frijda 1992; Shweder 1993), one's experienced and/or anticipated bodily sensations from the event, and the perceived sequence of actions one needs to take to enhance or mitigate the experience (i.e., plans of emotion regulation; goals and norms associated with emotions; Vishkin et al. 2023). Compared to people with low emotional granularity, those with high emotional granularity have developed a more diverse set of mental representations associated with different emotional experiences and thus categorize similarly valenced emotional experiences into a broader set of categories using different emotion labels (Barrett 2006).

As an example, Barrett (2006) reports how two study participants responded to the events of September 11, 2001. *Participant A* said, "My first reaction was terrible sadness ... But the second reaction was that of anger, because you can't do anything with the sadness." However, *Participant B* said, "I felt a bunch of things I couldn't put my finger on. Maybe anger, confusion,

fear. I just felt bad on September 11th. Really bad.” *Participant A* clearly distinguished between the two negative emotions of sadness and anger and differentiated between contextual cues associated with each (e.g., greater actionability associated with anger than sadness). However, *Participant B* did not distinguish between sadness, confusion, and fear, and used these labels interchangeably to refer to a general sense of unpleasantness. Thus, *Participant A* demonstrates higher emotional granularity than *Participant B*, despite the fact that *Participant B*, in fact, uses more emotion labels than *Participant A* to describe their experience.

Granularity in Negative Emotions and Coping Success

Prior research has primarily investigated the link between emotional granularity and coping success at the trait level by using experience sampling methods to measure emotional granularity. Experience sampling involves prompting participants several times a day for an extended period (e.g., often several days to a few weeks) to rate the degree to which they feel a set of predetermined emotions at the time of the prompts (e.g., Barrett et al. 2001). The method relies on the idea that different life situations are unlikely to all produce the same set of emotions. Thus, if a person’s ratings of their similarly valenced emotions correlate with each other across different life situations, the person cannot differentiate between emotions or emotional contexts of similar valence and has low emotional granularity. Using this method, researchers assess participants’ trait-level emotional granularity to investigate its outcomes.¹

¹ Some previous research has also attempted to measure emotional granularity using personality scales whereby participants self-report their perceived emotional granularity using items such as “I am aware of the subtle differences between feelings I have” (Kang and Shaver 2004). However, measurement of the construct using personality items has been less successful (Hoemann et al. 2021) because participants do not have accurate perceptions about themselves (Dunning, Heath, and Suls 2004; Nisbett and Wilson 1977).

Importantly, given the qualitative difference between positively and negatively valenced emotional experiences, researchers have usually investigated the effects of granularity in negative and positive emotions separately (e.g., Barrett et al. 2001). This body of research suggests that granularity in *negative* emotions is associated with a range of outcomes related to emotion regulation and coping, and thus impacts individuals' psychological health and well-being. For example, higher negative emotional granularity is associated with better regulation of intense negative emotions (Barrett et al. 2001). Intense negative emotions are also less likely to be associated with alcohol abuse among individuals with high granularity in negative emotions (Kashdan et al. 2010). Furthermore, higher granularity in negative emotions predicts lower impulsivity among individuals with borderline personality disorder (Tomko et al. 2015). Higher granularity in negative emotions is also associated with higher ability in adolescents to cope with stress exposure and their lower depression likelihood (Starr et al. 2019).

It is theorized that granularity in negative emotions is associated with successful coping because the broader set of mental representations of negative emotions that comes with high negative emotional granularity, also includes a broader set of coping strategies, which can be tapped into when needed (Barrett and Gross 2001). Notably, positive emotions do not necessitate coping in the first place, and are less likely to produce a parallel association with coping success.

While extant research has primarily investigated the association between negative granularity and coping at the trait level, one can also conceptualize the construct at the situation level. In reality, previous conceptualizations of the construct account for situation-level variance in emotional granularity: even when emotional granularity is considered as an individual-level skill, one can agree that individuals' ability and/or motivation to *use* this skill varies from one situation to another. Thus, situation-level variances in experiencing and/or recalling one's

emotions granularly have been previously theorized (Barrett and Gross 2001) and, recently, methods have been proposed for the assessment of within-person changes in emotional granularity using experience sampling data (Erbas et al. 2022). However, there is no prior empirical evidence showing that an individual would more successfully cope with a specific negative experience if they used negative emotion labels more (vs. less) granularly to describe this experience (i.e., *situation-level* analysis). Thus, our research is the first to test the association between negative emotional granularity and coping success at the situation level through language use, and to study the implications of this association in terms of how consumers rate businesses on online review platforms following unpleasant experiences.

Granularity in Negative Emotions, Coping Success, and Online Review Ratings

The rating (usually on a 5-star scale) that a consumer posts on review platforms indicates a *decision* that they make about the business after a consumption experience (Sridhar and Srinivasan 2012). This decision is subject to various psychological processes and is not merely an objective score of the negativity or positivity of the experiences. Consistent with this argument, previous research has shown that beyond the quality of the experience itself, processes related to social influence and conformity (Goes, Lin, and Au Yeung 2014; Moe and Trusov 2011; Sridhar and Srinivasan 2012), psychological distance (Huang et al. 2016), the design of the review platform (Aerts et al. 2017), and reviewer status (Zhang, Wei, and Zeng 2020) influence customer ratings.

While the role of coping in consumer decision making has been explored extensively (e.g., Duhachek 2005; Duhachek and Kelting 2009; James, Handelman, and Taylor 2011;

Raghunathan, Pham, and Corfman 2006), to the best of our knowledge, previous research on online reviews has not considered how coping affects consumers' online review ratings. Still, one expects consumers' successful coping with negative consumption experiences to impact their ratings of the business: the more successfully consumers cope with the negative emotions caused by an unpleasant service experience, the less likely they are to use these emotions in their decision when rating the business; thus, they will rate the business more positively (Raghunathan and Pham 1999; Raghunathan et al. 2006).

On this basis, given our proposition that granularly describing one's negative emotions resulting from an unpleasant experience is associated with more successful coping with the experience, we propose that, particularly when the overall experience has been negative (i.e., when coping is relevant), granularity in describing *negative* emotions in the online review text will be associated with a more positive rating of the business.

While the main focus of our research is to investigate how situation-level negative granularity impacts decisions, following our situation-level proposition above, one may also wonder whether trait-level differences in negative emotional granularity produce similar results. In other words, does a reviewer's propensity to demonstrate negative granularity in their online reviews predict their rating of specific reviews similarly to what we predict above? An affirmative answer to this question is important from a targeting standpoint because it suggests that marketers may use reviewers' negative granularity on review platforms as a psychological targeting/profiling tool (Matz and Netzer 2017; Matz et al. 2017). For example, a marketer may solicit reviews (e.g., through email campaigns) only from reviewers who tend to demonstrate higher negative granularity in their online reviews on the platform. Thus, following our situation-level proposition above, we also propose that reviewers who, on average, demonstrate higher

negative granularity across their reviews on the platform will provide more positive ratings for experiences that have been negative overall.

Reviewers' History of Writing Reviews

As explained, emotional granularity is conceptualized as a learned skill (Hoemann et al. 2021). That is, individuals' ability to differentiate between negative emotions (and cope with them) is thought to stem from the specificity of the mental representations they have developed for different negatively valenced emotions (Barrett 2006). This ability is expected to improve with *practice*. Consistently, recent evidence shows that participants in experience sampling studies demonstrate greater emotional granularity in the later stages of the study than in the early stages (Erbaş et al. 2018; Hoemann, Barrett, and Quigley 2021), presumably because the practice of rating their various emotions several times a day helps participants build the mental representations to differentiate their emotions from one another. Research has also shown that classroom exercises that enable students to learn about nuanced differences between emotional labels improve students' emotion regulation abilities and academic performance (Brackett, Rivers, Reyes, and Salovey 2012).

However, there is no evidence in the literature that consumption-related activities, such as the commonly experienced activity of writing reviews online, would help consumers improve their emotional coping skills. Still, reviewing products and services, which (in part) involve recalling, describing, and justifying one's negative emotions to a broader audience, may serve as a practice that hones the reviewer's emotional skills. Thus, we predict that as reviewers write

more reviews on a review platform, they will progressively describe their negative emotions more granularly in their reviews.

Furthermore, consistent with our previous prediction that the ability to describe negative emotions granularly is associated with coping, we predict that, particularly when the overall experience with a business is negative (when coping is relevant), the more extensive history of reviewing that the reviewer has at the time of writing the review, the more positive rating they will give to the business. Importantly, here we operationalize reviewers' history of writing reviews as the total number of previous reviews written by a reviewer at the time of writing each review, which increases as they write more reviews. Extant research has investigated the effect of platform-defined expertise (earning badges, etc.) (Nguyen et al. 2020; Tamaddoni et al. 2023; Zhang et al. 2020) and self-selection effects of prolific versus non-prolific reviewers (Schoenmueller, Netzer, and Stahl 2020) on review ratings. However, to the best of our knowledge, the progression of reviewers' history in writing reviews as a predictor of review rating has not been investigated.

Temporal Distance

Although the attitudes and memories that are formed as a result of emotions do persist (Rocklage and Luttrell 2021), a person's emotional reaction to an event is expected to become less visceral over time (Chang and Pham 2013; Ekman and Davidson 1994). Thus, one may expect that those reviewers who have waited longer from the time of receiving a service to the time of reviewing the business will be better able to analyze the contexts in which their emotions were evoked by a service experience. Therefore, we propose that greater temporal distance

between the time of receiving a service and the time of reviewing the business (hereafter, “temporal distance”) will be associated with more granularity in describing negative emotions in the review text. Consequently, this increased granularity should contribute to more successful coping with negative experiences. Thus, we propose that when the overall experience is negative (i.e., where coping is relevant) a greater temporal distance will be associated with a more positive rating of the business.

We should note that the effect of temporal distance on review rating has been investigated in previous research. Specifically, Huang et al. (2016) has shown that greater psychological distance, including temporal distance between the experience and the review, increases the positivity of ratings. Our research diverges from Huang et al. (2016) by recognizing the role of coping and emotional granularity in this effect, and predicting that the effect of temporal distance on the positivity of the reviews is particularly strong when the overall experience is negative and thus, coping is relevant.

In the following, we will first explain our deep-learning-based method for measuring emotional granularity in language use, followed by two pilot studies that validate our method and demonstrate the association between negative emotional granularity and coping success, and two main studies that test our predictions using two large online review datasets.

MEASURING EMOTIONAL GRANULARITY THROUGH TEXTUAL DATA

As explained, experience sampling, which for the past three decades has been the main method used to measure emotional granularity (e.g., Larsen and Cutler 1996), produces a trait-level assessment of individuals’ emotional granularity, which is not ideal for addressing

situation-level research questions. The method also requires a high degree of participant involvement, which is problematic in the applied field of marketing because it reduces the actionability of the construct in practice. Finally, to avoid participant fatigue, only a finite set of emotion labels can be used in experience sampling, which limits the range of emotions that can be captured using this method. Given the limitations of experience sampling, there have been calls in psychological research to develop methods that directly infer individuals' emotional granularity from their language (Kashdan, Barrett, and McKnight 2015). Furthermore, in the marketing domain, there has been an increasing interest in relying on the richness of the unstructured consumer-generated textual data to study consumer behavior (Berger et al. 2019; Packard and Berger 2023).

We suggest that given the close relationship between the conceptualization of emotional granularity and language, one can measure how granularly people describe their emotions by using advanced natural language processing (NLP) methods to systematically analyze how people use emotion labels in their language. Here, an individual who has used multiple emotion labels to describe their emotions would be considered to have used these emotional labels granularly only if they have applied them in different contexts. However, using different emotion labels in similar contexts suggests low emotional granularity, because it suggests that the labels have been used interchangeably. To elaborate, consider the emotional labels used by the two participants from Barrett (2006) discussed earlier: *Participant A*, has used “sadness” and “anger” in more differentiated contexts (high granularity), whereas *Participant B*, despite using more emotion labels, has used these labels all in a similar context (low granularity). Notably, emotional granularity is not necessarily associated with the number of emotional labels used, but rather describes the context differentiation between these labels when different labels are used.

Importantly, given the qualitative difference between negative and positive emotions, one should measure granularity for negative and positive emotions separately. Thus, to measure how granularly a person has described their negative emotions in their language, one should consider each unique negative emotion label that the person has used, code the language context in which each of these labels have been used, and finally calculate the degree of differentiation between these language contexts. Hence, lower context differentiation suggests lower negative emotional granularity and higher context differentiation suggests higher granularity. As detailed below, we develop a deep-learning-based method (using BERT feature vectors; Devlin et al. 2018) based on this idea to measure emotional granularity via language.

Calculating Negative Emotional Granularity

BERT Embeddings as Context Encodings. Core to our method is the use of the *Bidirectional Encoder Representations from Transformers* (BERT) model (Devlin et al. 2018) to summarize or “encode” the context surrounding each word used in a given text into a feature vector, which may be considered as a meta-summary of that word’s context. To elaborate, BERT is a deep-learning-based Large Language Model (LLM) that was trained, in part, by masking a random selection of 15% of the words in a large corpus of text and predicting each masked word using its adjacent words (i.e., its context). One part of the BERT model is an encoder, which models the context surrounding a given word into a 768-dimensional feature vector. In our research, we use this encoder model. BERT also includes a decoder which uses this context encoding to make predictions. However, the decoder is not used in our method. The BERT model, which is the first widely used LLM, has been described in extensive detail elsewhere

(Devlin et al. 2018) and is widely implemented in industry and academia. For brevity, its architectural specifications are not described here.

However, we should note that the BERT encoder produces a different feature vector for each word in a text, based on the focal word's surrounding words (i.e., its context). BERT produces different feature vectors even for identical words that are used in different contexts because the encoder is trained to encode the information that the decoder needs in order to predict the focal word based on its surrounding words. As such, BERT encodings are fundamentally different from “word embeddings” produced by various other models such as Word2Vec (Mikolov, Chen, Corrado, and Dean 2013) and GloVe (Pennington, Socher, and Manning 2014), which have been used in earlier consumer behavior research (Berger et al. 2019). In Word2Vec and GloVe, a word's embedding is an average representation of that word across the entire training corpus. Thus, these models produce the same embedding for identical words regardless of the context in which the word is used. However, BERT produces the feature vector representing a word's context, which is needed to predict the target word. This is why for two identical words that are used in different contexts, BERT produces different feature vectors.

Thus, the first step in our method involves feeding each piece of text (e.g., the text of a review) into a pre-trained BERT encoder model and producing the feature vector associated with each word within the text as a meta-summary of the context in which the word is used.

Dictionary of Emotion Labels. Distinguishing words that describe an emotion (e.g., “happy,” “apprehensive,” “hesitant”) from words that do not requires a glossary of emotion labels. An initial survey of the literature revealed that such a glossary is not readily available. For example, the Linguistic Inquiry and Word Count (LIWC) software (Pennebaker et al., 2001; Tausczik and Pennebaker 2010) includes a dictionary of words with positive and negative

associations, but not emotion labels per se. While some of the words in the LIWC dictionary are emotion labels (e.g., “sad,” “defensive”), others are not (e.g., “rapist,” “protest,” “harmful”). Similarly, the Evaluative Lexicon (Rocklage, Rucker, and Nordgren 2017) provides a dictionary of evaluative adjectives such as “wonderful” and “fantastic” which, although are rated on emotionality are not themselves emotion labels.

We thus relied on a language expert (with a PhD in linguistics) to produce a list of English words that describe emotions, and to denote (code) whether the word describes a positive or a negative emotion. A list of 1,379 negative and 887 positive emotional labels was thus generated.²

Categorizing words into Non-Emotional, Negative, and Positive labels. The next step of our method involves placing each word from a given piece of text (e.g., a review) into one of the following three categories: (1) non-emotional (does not match any word in our glossary), (2) negative (matches a negative-emotion label), or (3) positive (matches a positive-emotion label). To match words, we use their stemmed version (the Snowball stemming algorithm). We do not categorize words if they are one of the stop words commonly used in English (e.g., “this”, “and”, etc.).

Computing Negative Granularity. We use the Cronbach alpha statistic to capture the degree of differentiation between the contexts in which a set of words are used, such that a *higher* Cronbach alpha of the feature vectors of a set of words would suggest *lower* context differentiation between them. Thus, for each given text (i.e., for each review), we compute the Cronbach alpha associated with all the unique *negative* emotion labels used in that text to compute the degree of differentiation (non-interchangeability) between the negative emotion

² This glossary is available at https://osf.io/qe7t4/?view_only=6aa4d30b70ca445680bc76e7d6d0f69b.

labels used in the text. The use of the Cronbach alpha in our method is novel. While previous work in NLP research often uses cosine/Euclidian vector similarity scores to calculate the distance between *two* vectors (Berger et al. 2019), we use the Cronbach alpha to calculate the degree of differentiation of *two or more* items. Furthermore, Cronbach alpha calculates the shared variance among the different items (i.e., emotion labels) *relative to the total variance*, in which we are interested. For ease of interpretation, we subtract this statistic from 1 so that a higher score indicates higher differentiation and granularity, suggesting that if multiple negative emotion labels are used in the text, they represent different contexts. To continue with the example of the two participants in Barrett (2006), as shown in Figure 1, using our method, *Participant A*’s negative emotional granularity score (.25) is higher than that of *Participant B* (.14), which is consistent with our expectation. Notably, calculating negative emotional granularity for each text is possible if at least two negative emotion labels are used in that text.

FIGURE 1

MEASURING EMOTIONAL GRANULARITY THROUGH LANGUAGE

Participant A: “My first reaction was terrible sadness....But the second reaction was that of anger, because you can’t do anything with the sadness.”

Item 1: “sadness”	Item 2: “anger”
$f_{1,1}$	$f_{2,1}$
$f_{1,2}$	$f_{2,2}$
$f_{1,3}$	$f_{2,3}$
...	...
$f_{1,766}$	$f_{2,766}$
$f_{1,767}$	$f_{2,767}$
$f_{1,768}$	$f_{2,768}$

$$G^N = 1 - \alpha^N = .25$$

Participant B: “I felt a bunch of things I couldn’t put my finger on. Maybe anger, confusion, fear. I just felt bad on September 11th. Really bad.”

Item 1: “anger”	Item 2: “confusion”	Item 3: “fear”	Item 4: “bad”
$f_{1,1}$	$f_{2,1}$	$f_{3,1}$	$f_{4,1}$
$f_{1,2}$	$f_{2,2}$	$f_{3,2}$	$f_{4,2}$
$f_{1,3}$	$f_{2,3}$	$f_{3,3}$	$f_{4,3}$
...
$f_{1,766}$	$f_{2,766}$	$f_{3,766}$	$f_{4,766}$
$f_{1,767}$	$f_{2,767}$	$f_{3,767}$	$f_{4,767}$
$f_{1,768}$	$f_{2,768}$	$f_{3,768}$	$f_{4,768}$

$$G^N = 1 - \alpha^N = .14$$

Note. An example of how our method captures the negative emotional granularity in a given text, using how *Participants A and B* from Barrett (2006) explained their emotional reaction to September 11, 2001. For a given text, we use a 768-dimensional feature vector (f_i) to encode the context in which each negative emotion label is used. We then compute the Cronbach alpha of all these feature vectors. Negative granularity of that text is computed by subtracting the Cronbach alpha from 1. Using this method, *Participant A* (more granular) receives a higher granularity score than *Participant B*. The feature vectors of two identical emotional labels that are used in different contexts will differ from one another because their contexts are different.

Computing Positive Granularity. Following the same steps as above, we compute a measure of granularity in positive emotions by considering only the positive emotion labels in the text. While the central focus of our research is to investigate the effects of granularity in negative emotions, in our empirical analyses we also compute a measure of positive granularity as a control variable.

PILOT STUDY 1: VALIDATION OF OUR MEASUREMENT APPROACH

The purpose of pilot study 1 was to evaluate our proposed method for calculating the emotional granularity in language by comparing it with the commonly used experience-sampling-based measurement of emotional granularity, which is currently the predominant method being used to measure emotional granularity in psychological research. Given the high cost of collecting primary data in experience sampling, we obtained the relevant data from authors of previously published research (Hoemann et al. 2020; Hoemann, Khan, et al. 2021; Hoemann, Barrett, et al. 2021; Hoemann et al. 2023). We thank the original authors (who are not among the authors of the current manuscript) for generously sharing their data with us.³ This data includes measurements of participants' trait-level emotional granularity based on experience sampling, in addition to participants' descriptions of their daily experiences over several days. We computed a trait-level deep-learning-based emotional granularity score for each participant by calculating the average granularly with which they described their emotional experiences during the course of the study. We tested whether our deep-learning-based emotional granularity

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score was correlated with the experience-sampling-based emotional granularity scores computed by the original authors who collected the data. We reasoned that if our measure indeed captures participants' situation-level emotional granularity, as a conservative test, the average of these situation-level emotional granularity scores should capture participants' trait-level dispositions, which should be correlated with the trait-level scores produced using the experience sampling method.

Method

The data was collected from 50 participants (54% female; $M_{Age} = 22.5$, $SD = 4.4$ years) who were fluent in English and were recruited through advertisements in the greater Boston area. Participants received \$490 for completing all parts of the study, plus up to \$55 in compliance and task incentives. They completed approximately 14 days ($M = 14.4$, $SD = 0.6$) of experience sampling, including peripheral physiological monitoring and end-of-day diaries. Only the end-of-day diary data are relevant here.

On each day of the study, participants wore physiological sensors for about eight hours. Information from these sensors was used to automatically prompt participants to respond to several questions via an associated smartphone application (app). The prompts occurred whenever participants experienced a substantial, sustained change in cardiac activity in the absence of movements. Participants also received two random prompts each day that were not triggered by physiological measures. Altogether, participants responded to an average of 8.65 prompts ($SD = 1.09$) per day. At each prompt, participants responded to a series of questions presented on the smartphone app, which included describing in a few words what was going on

at the time, along with their social context, and categorizing their main activity into a set of predefined activities (e.g., “socializing,” “eating,” “working”). At the end of each day, this information was used to remind participants of the event associated with each prompt and to probe them further about the event. Specifically, immediately upon finishing each day of experience sampling, participants received an online end-of-day diary. In this diary, they were reminded of the activity associated with each of that day’s prompts using the information they had provided on the smartphone app. For each activity, participants were asked to describe in more detail what was happening when they received the prompt. Furthermore, for every event, using items ranging from 0 (‘not at all’) to 6 (‘very much’), participants rated the extent to which the event made them experience a set of eight negative emotions (“afraid,” “angry,” “bored,” “disgusted,” “embarrassed,” “frustrated,” “sad,” “worn out”) and 10 positive emotions (“amused,” “calm,” “excited,” “grateful,” “happy,” “neutral,” “proud,” “relieved,” “serene,” “surprised”).

For each participant, an experience-sampling-based emotional-granularity score was calculated using the participant’s ratings for the 18 emotion adjectives collected in the end-of-day diaries. To this end, an intraclass correlation (ICC) for consistency with averaged raters (i.e., ‘C-k’ method) was used where higher ICC values reflect lower emotional granularity (i.e., greater shared variance among adjectives’ ratings). Separate estimates of granularity were computed for the negative and positive emotions and were then averaged to obtain a total emotional granularity score. ICCs were z transformed and then multiplied by -1 so that lower values reflected lower granularity, and higher values reflected higher granularity. Note that we obtained each participant’s pre-calculated emotional granularity scores from the original authors.

To compare the emotional granularity scores produced by our proposed method with the scores obtained from the above experience-sampling-based method, we used the textual data from participants' 5,832 descriptions ($M = 117$, $SD = 23$, $\text{min} = 61$, $\text{max} = 172$ per participant) of the events associated with each prompt. For each of these texts, we calculated the degree of granularity in participants' descriptions of their negative emotions and the granularity in their positive emotions from the event, using our deep-learning-based method described earlier. Many descriptions did not meet the minimum requirement of having at least two positive and/or at least two negative emotion labels. This limitation prevented us from calculating the positive and/or negative emotional granularity of these descriptions (note that these descriptions varied in length, and participants had not been explicitly instructed to describe their emotions). Hence, we were able to calculate negative granularity scores for only 2,390 of event descriptions and positive granularity scores for 3,214 descriptions (but were still able to calculate granularity scores for all participants). Given this limitation in the data, which reduced the sensitivity of our test, we focus on participant's average granularity score (average of their granularity in positive and negative emotions) in our analysis in this study. Thus, we calculated each participant's deep learning-based granularity score by averaging all their (positive and negative) granularity scores.

Results and Discussion

We observed a positive correlation between participants' experience-sampling-based emotional granularity score and their emotional granularity scores obtained from our deep-learning-based method ($r = .39$, $p = .005$). This result supports the notion that our deep-learning-

based method of calculating emotional granularity through language, taps into the emotional granularity construct explored in previous research.⁴

PILOT STUDY 2: EMOTIONAL GRANULARITY AND COPING SUCCESS

The purpose of pilot study 2 was to investigate whether emotional granularity in describing the negative emotions evoked by an unpleasant experience is indeed associated with coping with that experience. Since it is important to test the association between emotional granularity and coping success by examining participants' meaningful and genuine descriptions of their emotional experiences, we investigated this association in a domain that would be commonly meaningful to the student participants available to us. Thus, we deviated from the domain of investigation of our research (i.e., online reviews) and tested the association in the domain of exam-related stress among university students, which is a commonly experienced and emotionally taxing situation for this target population. We asked students to describe, in an open-ended essay, the negative emotions they experience as a result of taking exams and then to self-report how well they cope with exam-related stress. We then tested whether the granularity in the descriptions of negative emotions associated with exams was correlated with self-reported success in coping with exam-related stress.

⁴ The correlation between the experience-sampling-based and our deep-learning-based granularity scores was significant for positive emotions ($r = .28, p = .047$) but not significant for negative emotions ($r = .18, p = .215$), which we attribute to reduced sensitivity in the data resulting from high number of missing negative emotional granularity scores, but acknowledge as a limitation of this study.

Method

A total of 560 undergraduate students ($M_{\text{Age}} = 20.48$, $SD = 1.67$, 46% female) from a large public university in the US participated in this study for course credit. Participants were asked to *“take a few minutes to consider some of your previous experiences taking tests/exams at the university. Think about the various negative emotions that you felt before, during, and after the exam. Then take about 5 minutes to write down what negative emotions you felt and why you felt them. In your writing, please use as many emotion labels as possible to describe the different feelings that you experienced.”* Participants were then given as much time as needed to write their essay. After completing this task, participants self-reported the extent to which the following sentences reflect their experience when taking exams (using five-point items ranging from “strongly disagree” to “strongly agree”): (1) “I feel confident and composed when taking exams even in high-pressure situations.” (2) “I am able to effectively control and reduce my stress and anxiety levels before and during the exam.” (3) “I can stay focused and maintain my composure when unexpected challenges or distractions arise when I am taking exams.” (4) “I am able to remain calm before and during exams.” (5) “I am skilled at managing my emotions and maintaining a positive attitude when I encounter challenging questions during the exam.” These items were averaged as an index of self-reported success in coping with exam-related stress ($\alpha = .89$). Participants then stated their age and gender. In addition, the recruitment process in our behavioral lab allowed some participants to participate twice in the study. Thus, at the end of the study we asked participants if they had previously participated in the study. A total of 26 responses which were retakes were removed from the sample prior to any data analysis.

Results

We calculated a negative granularity score for each essay using our proposed method. A total of 96 essays had less than two negative emotion labels. Thus, a negative granularity score was not calculated for them, leaving us with 464 essays with negative granularity scores. We observed a positive association between negative granularity scores and self-reported success with coping ($r = .19, p < .001$).

We also conducted additional analysis to test the robustness of this correlation. To determine whether our negative granularity scores explained coping success beyond what would be deduced from simply considering the sentiment of the essays, we also calculated the sentiment of the essays using LIWC software. LIWC is a well-established dictionary-based text analysis software for sentiment calculation (Pennebaker et al. 2001; Tausczik and Pennebaker 2010) and has been used extensively in previous research (e.g., Goranson et al. 2017; Ludwig et al. 2013). LIWC estimates have been shown to correlate with human raters' (Bantum and Owen 2009). The software includes a dictionary of words with positive and negative associations (but, as mentioned before, not emotion labels per se). To compute sentiment, we subtracted the percentage of words with negative associations from the percentage of words with positive associations in each essay. In addition, we computed the number of unique negative and positive emotion labels used in each essay. Furthermore, to test whether the association is driven by participants' engagement levels, we computed the length (word count) of the essays as a proxy for participant engagement. A regression analysis predicting self-reported coping success with all these variables produced only a significant effect of negative granularity ($\beta = 0.148$, S.E. =

0.054, $t = 2.76$, $p = .006$, 95% CI = [0.043, 0.253]) and number of unique positive words ($\beta = 0.169$, S.E. = 0.066, $t = 2.56$, $p = .011$, 95% CI = [0.039, 0.299]) (all other p -values $> .170$).

We should note that because participants were given explicit instructions to write about negative emotions, unsurprisingly, 274 participants did not use two or more positive emotion labels in their essays. The addition of positive granularity scores, as a predictor, to the regression above (with 255 observations, given missing values on the negative and positive granularity scores) yielded only a significant effect of negative granularity ($\beta = 0.199$, S.E. = 0.070, $t = 2.83$, $p = .005$, 95% CI = [0.060, 0.338]). Unsurprisingly, positive granularity was not associated with higher coping success ($\beta = -0.146$, S.E. = 0.082, $t = -1.76$, $p = .078$, 95% CI = [-0.308, 0.017]) (all other p -values $> .117$), because coping is not relevant when emotions are positive.

Discussion

The results of pilot study 2 demonstrated that the granularity with which students describe their negative emotions about exams uniquely predicts their self-reported success in coping with exam-related stress. The extant research in psychology has demonstrated the link between negative emotional granularity and coping success using experience sampling methods (e.g., Barrett et al. 2001). However, the results of pilot study 2 are the first in the literature to show that negative emotional granularity that is measured unobtrusively through language use can also predict coping success. With the next two studies, we tested the implications of the association between granularity in negative emotions and coping success in the context of consumer decisions in online review ratings of unpleasant service experiences.

STUDY 1: EMOTIONAL GRANULARITY, REVIEWING HISTORY, AND REVIEW RATINGS

The purpose of study 1 was to test our propositions regarding the relationship between reviewing history, granularity in describing negative emotions in the review text, and review ratings. We used a large dataset of online consumer reviews from Yelp.com, one of the largest online review platforms in the world, to test the proposed effects. We collected over 11 million reviews from over 52,000 Yelp reviewers, ensuring that if our dataset included one review from a reviewer, it also included all their other reviews.

First, we predicted that higher granularity in describing negative emotions in the review text is associated with a more positive rating of the business, but more so when the overall experience with the business is negative. To test this proposed effect, we investigated how the sentiment expressed in the review text, as a measure of the reviewer's overall experience with the business, and the granularity with which negative emotions are described in the review text, interact to predict the 5-star rating given in the review.

Second, we also investigated whether trait-level differences in negative granularity produce results similar to those predicted above. Therefore, we tested whether reviewers who had on average demonstrated higher negative granularity across all their reviews on the platform give more positive ratings for experiences that have been overall negative.

Third, building on prior research, which views emotional granularity as a skill, we predicted that as reviewers write more reviews, they will progressively describe their negative emotions more granularly in their review. To test this prediction, we investigated how reviewers' reviewing history at the time of writing a review, as measured by the number of reviews a

reviewer has authored on the platform prior to writing the focal review, predicts the granularity with which they describe negative emotions in the focal review.

Fourth, following the predicted relationship between reviewing history and negative emotional granularity, as well as the previously predicted relationship between negative emotional granularity and coping success, we tested the proposition that as reviewers progressively write more reviews on the online review platform, they will progressively provide more positive ratings, particularly for negative consumption experiences, in which coping is relevant.

Review Data

The data for this study was gathered from Yelp. Yelp enables users to share and evaluate their experience with service providers in the form of qualitative textual comments and a star rating on a 5-point scale. The platform also allows users to create a profile and to follow other users and be followed by them. We adopted a snowball sampling approach (Zhang, Wei, and Zeng 2020) to create our dataset. As the first step, we began with one prolific reviewer on Yelp and collected all reviews written by this individual. In the second step, from this reviewer's profile, we extracted the list of their friends and collected all reviews written by a random sample of 20% of them. Finally, from the reviewers in our second step sample, we identified a random sample of 20% of their friends and collected all their reviews. This sampling approach ensured that we had all the online reviews that each reviewer in our dataset had written. Given that our text analysis approach was limited to English, we removed all non-English reviews from our

dataset. Through this process, we obtained 11,272,282 reviews, written by 52,804 reviewers, in a period between July 2000 and September 2021.

Measures

Granularity in Negative Emotions. Using the proposed method explained earlier, for each review, we computed the granularity with which the reviewer has described their negative emotions in that review using our method explained earlier. Since some reviews contained less than two negative emotion labels, a total of 5,526,643 reviews received a negative granularity score.

Overall Experience (Review Sentiment). As a measure of the reviewer's overall experience with the business, we computed the sentiment of each review using the LIWC software (Pennebaker et al. 2001) by subtracting the percentage of words with negative associations from the percentage of words with positive associations in each review.

Trait- Level Reviewer Negative Granularity Index. For our trait-level analysis, we computed a trait-level negative granularity index by computing the average of all negative granularity scores for all reviews written by each reviewer.

Reviewing History. We computed a reviewer's reviewing history at the time of writing each review by counting the number of reviews that the individual had written prior to the focal review. For model estimation, this variable was log-transformed.

Control Variables. As control variables we computed the number of unique positive and unique negative emotion labels used in the review, as well as the word count of each review. As another control variable, we computed the granularity with which the reviewers described their

positive emotions in their review text. Coping is not relevant in the case of positive emotions. Thus, we did not expect the results for granularity in positive emotions to be similar to the granularity in negative emotions. We used the same method that was used to compute granularity in negative emotions to compute granularity in positive emotions (but this time by considering positive emotion labels). Again, some reviews contained less than two positive emotion labels. Therefore, a total of 10,238,286 reviews received a positive granularity score. For our trait-level analysis, we also computed a trait-level positive granularity index by averaging all positive granularity scores for each reviewer.

Furthermore, similar to how we calculated positive and negative emotional granularity, we also calculated the degree to which the non-emotional words in a review are differentiated. This was done by applying our method to all non-emotional words in the review. We included this measure as a control variable because the differentiation between non-emotional words in the review may be considered a proxy for the variety of topics discussed in it, or the degree of sophistication of the language being used. For our trait-level analysis, we also computed a trait-level non-emotional differentiation index by averaging all non-emotional differentiation scores of each reviewer.

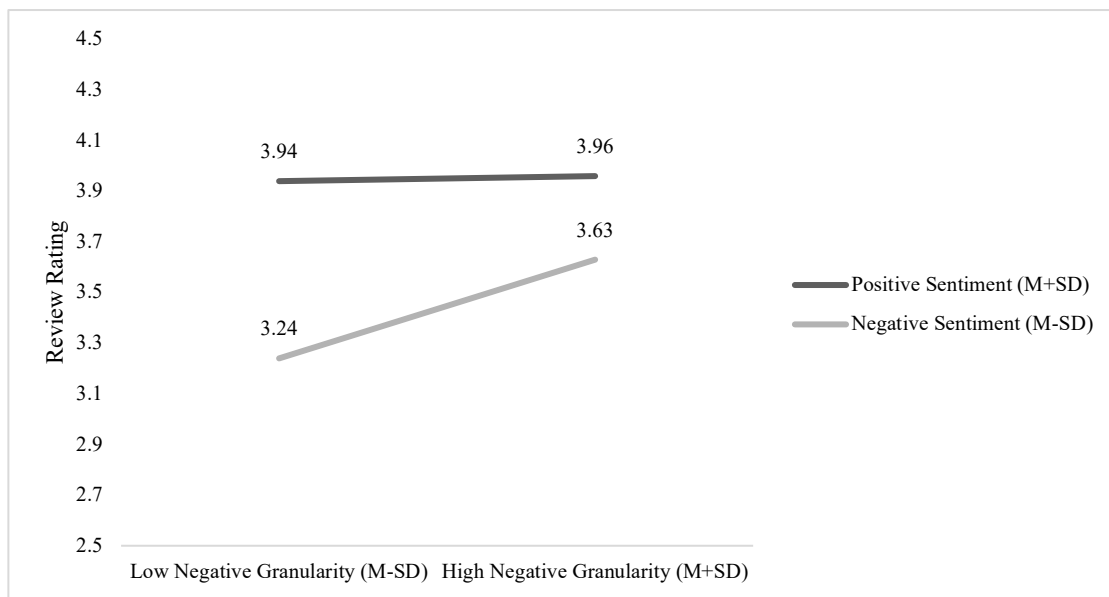
Analyses and Results

Situation-Level Negative Granularity in Review Text and Review Ratings. We conducted a multi-level regression (Model 1.1), predicting review rating with the fixed effects of negative granularity, sentiment, and the negative granularity \times sentiment interaction, while controlling for the fixed effects of positive granularity, degree of differentiation of non-emotional words, and

number of unique negative emotion labels, unique positive emotion labels, and the word count of the review. We also included the reviewer random intercept in the model. For the ease of interpretation of the results, we Z-score normalized all independent variables in this model and all subsequent models. The full results of this regression are presented in Table 1. For brevity, we discuss only the results that are central to testing our predictions.

FIGURE 2

THE IMPACT OF (SITUATION-LEVEL) NEGATIVE GRANULARITY AND SENTIMENT
ON REVIEW RATING



The results showed that, unsurprisingly, a more positive sentiment in the review text ($\beta = 0.256$, S.E. = 0.00, $t = 534.79$, $p = .000$, 95% CI = [.255, .257]) was associated with a more positive rating of the business. As predicted, the more granularly the reviewer described their negative emotions in the review text, the more positively they rated the business ($\beta = 0.101$, S.E. = 0.00, $t = 152.07$, $p = .000$, 95% CI = [.099, .102]). We had predicted that the effect of negative emotional granularity on rating would be stronger when sentiment, as a measure of overall

consumer experience, is negative because coping is most relevant to experiences that are negative overall. In support of this prediction, we observed a significant negative granularity \times sentiment fixed interaction effect ($\beta = -0.094$, S.E. = 0.00, $t = -211.07$, $p = .000$, 95% CI = [-0.094, -0.093]). As shown in Figure 2, simple slope analysis revealed that, in those reviews where the sentiment was negative (M-SD), the more granularly the reviewer described their negative emotions within the review text, the more positively they rated the business ($\beta = 0.19$, S.E. = 0.00, $t = 229.28$, $p = .000$). However, the effect of emotional granularity on rating was attenuated for reviews that had an overall positive sentiment (M+SD; $\beta = 0.01$, S.E. = 0.00, $t = 9.75$, $p = .000$).

TABLE 1
RESULTS OF MODELS 1.1 AND 1.2

Fixed Effects	Model 1.1		Model 1.2	
	DV: Rating		DV: Rating	
	β	t	β	t
Intercept	3.694	1923.73	3.919	2543.38
Situation-Level Negative Granularity	0.101	152.07		
Trait-Level Negative Granularity			0.074	64.16
Sentiment	0.256	534.79	0.204	652.02
Situation-Level Negative Granularity \times Sentiment	-0.094	-211.07		
Trait-Level Negative Granularity \times Sentiment			-0.043	-153.15
Unique Negative Labels	-0.129	-148.37	-0.312	-668.80
Unique Positive Labels	0.266	250.39	0.450	766.27
Word Count	-0.194	-169.60	-0.178	-242.63
Situation-Level Positive Granularity	-0.183	-246.50		
Trait-Level Positive Granularity			-0.104	-53.25
Situation-Level Non-Emotional Words Differentiation	-0.009	-14.36		
Trait-Level Non-Emotional Words Differentiation			0.035	20.07
Variance of Random Intercept	0.141		0.095	
Number of Reviews (Reviewers)	5,359,456 (51,044)		11,253,937 (51,428)	

Note. All p -values are significant below the .0001 level.

Interestingly, granularity in positive emotions was associated with more negative ratings ($\beta = -0.182$, S.E. = 0.00, $t = -246.5$, $p = .000$, 95% CI = [-.184, -.181]). This latter result was not a priori predicted. However, a post-hoc interpretation of it may be that describing one's positive emotions more granularly is associated with a higher likelihood of considering the representativeness and relevance of one's feelings for the judgement at hand (i.e., 'I enjoyed my coffee at this café but that was because the weather was nice'; Pham 1998), which may reduce the total sum of the impact of positive feelings on ratings. We discuss this interesting result in more detail in the General Discussion section.

Trait-Level Negative Emotional Granularity and Review Ratings. To investigate whether the effects found in Model 1.1 with situation-level negative granularity hold at the trait level, we conducted another multi-level regression (Model 1.2) that predicts the rating of each review with the fixed effects of that review's sentiment, the trait-level negative emotional granularity index of the reviewer of that review, and the interaction of these two factors. In this model, we also controlled for the fixed effects of the reviewer's trait-level positive granularity index, the reviewer's trait-level degree of differentiation of non-emotional words index, the number of unique negative and positive emotion labels in the review, and the word count of the review. We also included the reviewer random intercept in the model to capture the between-reviewer variances. The full results of this regression are also presented in Table 1. Consistent with our situation-level analysis from Model 1.1, we observed that reviewers' greater propensity for describing negative emotions in their online reviews was associated with more positive ratings ($\beta = 0.074$, S.E. = 0.001, $t = 64.16$, $p = .000$, 95% CI = [0.072, 0.076]). Importantly, as expected, this effect was moderated by the review's sentiment ($\beta = -0.043$, S.E. = 0.000, $t = -153.15$, $p = .000$, 95% CI = [-0.043, -0.042]): the effect of a reviewer's propensity for granularly describing

their negative emotions on positivity of review ratings was stronger if the focal review described a negative experience ($\beta = 0.12$, S.E. = 0.00, $t = 96.98$, $p = .000$) than if it described a positive experience ($\beta = 0.03$, S.E. = 0.00, $t = 27.03$, $p = .000$).

Reviewing History and Granularity in Describing Negative Emotions. We argued before that as reviewers write more reviews, they become better skilled at describing their negative emotions granularly, which suggests that we should observe an increase in negative emotional granularity as reviewers write more reviews. To test this effect, we conducted another multi-level regression (Model 1.3) to predict the granularity with which negative emotions are described in a review, with the fixed effects of the reviewer's review history (at the time of authoring that review), sentiment, and the review history \times sentiment interaction, while controlling for the fixed effects of positive granularity, the degree of differentiation of non-emotional words, the number of unique negative and positive emotion labels, and the word count of the review. We also included the reviewer random intercept in the model. The full results of this regression are presented in Table 2. As predicted, we observed a significant effect of reviewing history on granularity in negative emotions, showing that as reviewers wrote more reviews, they progressively described their negative emotions more granularly in their reviews ($\beta = 0.006$, S.E. = 0.00, $t = 16.43$, $p = .000$, 95% CI = [0.006, 0.007]).

Reviewing History and Review Ratings. Given the association between negative granularity and coping success, the progressive increase in reviewers' negative granularity in their reviews would predict that as reviewers write more reviews, they will progressively give more positive ratings, especially for negative service experiences where coping is relevant. To test this prediction, we conducted another multi-level regression (Model 1.4) that predicted the review rating, with the fixed effects of reviewing history, sentiment, and the reviewing history \times

sentiment interaction, while controlling for the fixed effects of positive granularity, the degree of differentiation of non-emotional words, the number of unique negative and positive emotion labels, and the word count of the review. We also included the reviewer random intercept in the model. The full results of this regression are also presented in Table 2.

TABLE 2
RESULTS OF MODELS 1.3, 1.4 AND 1.5

Fixed Effects	Model 1.3		Model 1.4		Model 1.5	
	DV: Neg. Granularity		DV: Rating		DV: Rating	
	β	t	β	t	β	t
Intercept	-0.010	-12.51	3.746	1875.30	3.771	1901.57
Negative Granularity					0.100	151.02
Reviewing History	0.006	16.43	0.094	152.75	0.093	152.42
Sentiment	0.056	178.34	0.248	516.78	0.253	527.40
Negative Granularity \times Sentiment					-0.093	-210.61
Reviewing History \times Sentiment	-0.003	-10.32	-0.028	-67.13	-0.027	-64.61
Unique Negative Labels	-0.870	-2106.47	-0.239	-380.13	-0.129	-149.02
Unique Positive Labels	0.003	3.69	0.028	261.69	0.264	248.84
Word Count	0.220	295.21	-0.170	-149.53	-0.193	-168.94
Positive Granularity	0.029	59.33	-0.173	-233.22	-0.182	-246.66
Non-Emotional Words Differentiation	0.036	81.36	-0.005	-7.046	-0.006	-8.70
Variance of Random Intercept	0.015		0.147		0.141	
Number of Reviews (Reviewers)	5,359,456 (51,044)		5,359,456 (51,044)		5,359,456 (51,044)	

Note. All p -values are significant below the .0001 level.

We observed a significant effect of reviewing history on ratings, showing that as reviewers wrote more reviews, they progressively provided more positive ratings ($\beta = 0.094$, S.E. = 0.00, $t = 152.75$, $p = .000$, 95% CI = [0.093, 0.095]). Importantly, we observed a significant reviewing history \times sentiment interaction effect as well ($\beta = -0.028$, S.E. = 0.00, $t = -67.13$, $p = .000$, 95% CI = [0.-029, -0.027]). Consistent with our coping-based arguments, the

association between reviewing history and ratings was stronger when the overall service experience, measured by sentiment, was negative (M-SD; $\beta = 0.12$, S.E. = 0.00, $t = 164.35$, $p = .000$) than when it was positive (M+SD; $\beta = 0.07$, S.E. = 0.00, $t = 88.20$, $p = .000$).

The Mediating Effect of Negative Granularity. We argue that the interactive effect of reviewing history and sentiment on ratings is driven by greater granularity in describing one's negative emotions. This argument suggests that negative granularity should mediate the reviewing history \times sentiment moderation effect on review ratings. The currently available packages for testing moderated mediation have difficulty processing our data due to its large size and multi-level nature. Therefore, we tested for moderated mediation following the consecutive-regressions method proposed by Muller, Judd, and Yzerbyt (2005). To this end, we conducted another multilevel regression (Model 1.5), which included all factors that were included in Model 1.4 plus the effect of negative granularity and the negative granularity \times sentiment interaction. The full results of this regression are also presented in Table 2. Based on Muller et al. (2005), to conclude moderated mediation, one should observe a significant reviewing history \times sentiment interaction effect in Model 1.4 and a significant effect of reviewing history in Model 1.3, which we have observed. Furthermore, one should also observe that the negative granularity \times sentiment interaction in Model 1.5 is significant, which we observe ($\beta = -0.094$, S.E. = 0.00, $t = -210.61$, $p = .000$, 95% CI = [-0.094, -0.092]). Furthermore, the magnitude of the reviewing history \times sentiment interaction in Model 1.5 should be reduced compared to Model 1.4, which we also observe ($\beta = -0.027$, S.E. = 0.00, $t = -64.62$, $p = .000$, 95% CI = [-0.028, -0.026]). These results suggest a moderated mediation, which is consistent with the notion that reviewing history increases the likelihood of granularity when describing negative emotions, which then

contributes to more positive ratings when coping is relevant (i.e., sentiment, as a measure of whether the overall experience is negative).

Discussion

In study 1, we used a large sample of reviews from reviewers on Yelp.com to conduct an analysis of the relationship between reviewing history, granularity in describing negative emotions in the review text, and reviewer ratings. First, we found evidence consistent with the notion that the granularity in describing negative emotions is associated with coping success. Coping is most relevant in situations where the overall service experience has been negative, and a measure of this overall negativity is the overall sentiment expressed in the reviews. Accordingly, we observed that especially for reviews with a negative sentiment, granularity in negative emotions is associated with more positive ratings of the business. We observed this effect at two levels. First, at the situation level, we observed that granularity in negative emotions in a specific review resulted in the above effect. Second, and at the trait level, we observed that a reviewer's average granularity in describing their negative emotions throughout the entire set of their reviews on the platform is associated with more positive ratings, particularly in regard to negative experiences. This trait level analysis is important because of its implications for consumer targeting and profiling. In addition, this effect is important because a trait-level negative granularity index is less likely to be affected by an unknown aspect of single reviews (some factor other than negative granularity).

We also found evidence consistent with previous research which has shown that negative granularity is a learned skill (Brackett et al. 2012; Erbas et al. 2018; Hoemann et al. 2021). We

observed that as reviewers progressively wrote more reviews, their negative granularity increased, which resulted in their more positive ratings, especially for negative experiences.

STUDY 2: EMOTIONAL GRANULARITY, TEMPORAL DISTANCE, AND REVIEW RATINGS

In the studies reported above, we investigated the extent to which the granularity in describing negative emotions is associated with coping success, the impact of this granularity on rating of service experiences that are overall negative, and the impact of skill and reviewing history on granularity. The main purpose of study 2 was to test our proposition that the temporal distance between a service experience and the writing of the review, as a situational factor, predicts the granularity with which reviewers describe their negative emotions in a review. We collected review data from TripAdvisor.com because this platform also provides information on when a review was posted and when the visit to the service provider took place. We tested the proposed effect that a greater temporal distance is associated with greater granularity in describing negative emotions in the review text. Furthermore, we investigated whether the increased negative granularity resulting from the greater temporal distance predicts a more positive rating of the business, especially when coping is most relevant: when the overall experience is negative.

Review Data

We collected data from TripAdvisor, one of the world's largest online travel platforms, which enables users to review hotels, restaurants, airlines, and cruises. Following previous research (Chevalier et al. 2018; Proserpio and Zervas 2017), we collected the entire set of reviews for all hotels in two major travel cities in the United States: New York and Las Vegas. This resulted in a total of 1,343,518 reviews spanning 18 years (2003–2020). Like Yelp, TripAdvisor enables users to share and evaluate their experience with service providers in the form of qualitative textual comments and a star rating on a 5-point scale. We collected the review text, the review ratings, when each review was posted, and when the visit to the service provider took place.

Measures

Temporal Distance. TripAdvisor provides the month when the visit to the service took place (e.g., Dec 2023). Thus, to measure temporal distance, we counted the number of months between the time of the visit and the date when the review was posted. This number was then log transformed for incorporation into the model. A total of 1,278 reviews produced a temporal distance that was negative, suggesting that the reviewer either reviewed the service before visiting it, or that the time of the visit was incorrect. These reviews were excluded from further analysis.

Review Sentiment. We measured the sentiment of each review using LIWC as a measure of overall positivity of the service experience using the method similar to the one used in study 1.

Negative Granularity. For each review, we computed the granularity with which the reviewer described their negative emotions using the method explained earlier. Given that some reviews included less than two negative emotion labels, a total of 514,679 reviews received a negative granularity score.

Control Variables. As control variables, we computed the number of unique positive emotion labels, negative emotion labels, and the total word count of the review. As in study 1, we also computed granularity in positive emotions as a control variable. Again, some reviews contained less than two positive emotion labels. Therefore, a total of 1,207,997 reviews received a positive granularity score. We also computed the degree to which all non-emotional words in a review are differentiated as we did in study 1. Since a number of reviews were very short, a total of 1,343,399 reviews received this score.

Results

The Effect of Negative Granularity and Sentiment on Review Rating. As a first analysis, we tested whether the results of the previous study on the relationship between negative granularity, sentiment, and review rating would be replicated with the current dataset. We conducted a regression (Model 2.1), predicting review rating with negative granularity, sentiment, and the negative granularity \times sentiment interaction, while controlling for positive granularity, the degree of differentiation of non-emotional words, the number of unique negative and positive emotion labels, and the word count of the review.

The full results of this regression are presented in Table 3. We focus on the results that are pertinent to testing our predictions. Unsurprisingly, a more positive sentiment ($\beta = 0.249$, S.E. =

0.001, $t = 179.89$, $p = .000$, 95% CI = [0.246, 0.251]) was associated with a more positive rating of the business. Replicating the results of the previous study, negative emotional granularity was associated with higher ratings ($\beta = 0.157$, S.E. = 0.002, $t = 88.44$, $p = .000$, 95% CI = [0.154, 0.161]). We again observed the predicted negative granularity \times sentiment interaction effect ($\beta = -0.089$, S.E. = 0.001, $t = -70.41$, $p = .000$, 95% CI = [-0.092, -0.087]). As in study 1, simple slope analysis revealed that in those reviews where sentiment was negative (M-SD), the more granularly the reviewers described their negative emotions, the more positively they rated the business ($\beta = 0.246$, S.E. = 0.002, $t = 106.92$, $p = .000$, 95% CI = [0.242, 0.251]). However, the effect of emotional granularity on rating was attenuated for reviews that had an overall positive sentiment (M+SD) ($\beta = 0.068$, S.E. = 0.002, $t = 33.01$, $p = .000$, 95% CI = [0.064, 0.072]).

TABLE 3
RESULTS OF MODELS 2.1, 2.2, AND 2.3

	Model 2.1		Model 2.2		Model 2.3	
	DV: Rating		DV: Neg. Granularity		DV: Rating	
	β	t	β	t	β	t
Intercept	0.023	18.67	0.000	0.02	0.000	-0.19
Negative Granularity	0.157	88.44				
Sentiment	0.249	179.89	0.075	66.75	0.139	151.55
Negative Granularity \times Sentiment	-0.089	-70.41				
Temporal Distance			0.013	13.56	0.027	35.67
Temporal Distance \times Sentiment			-0.001	-0.68	-0.028	-36.63
Unique Negative Labels	-0.094	-37.42	-0.912	-603.54	-0.391	-300.28
Unique Positive Labels	0.226	80.55	0.037	16.17	0.269	153.80
Word Count	-0.185	-61.18	0.301	123.86	-0.120	-61.16
Positive Granularity	-0.286	-149.39	0.17	10.70	-0.218	-198.16
Non-Emotional Words Differentiation	0.044	26.39	0.075	54.43	0.101	94.72
Number of Reviews	479,799		479,298		1,206,768	

Note. Except for the intercept in Models 2.2, the intercept in Model 2.3, and the temporal distance \times sentiment interaction in Model 2.2, all p -values are significant below the .0001 level.

The Effect of Temporal Distance on Negative Granularity. We predicted that a greater temporal distance increases reviewers' likelihood of describing their negative emotions granularly. To provide support for this prediction, we estimated Model 2.2, in which we predicted negative granularity with temporal distance, sentiment, and the temporal distance \times sentiment interaction as the main independent variables, while controlling for the effect of the same control variables that were included in Model 2.1. The full results of this regression are presented in Table 3. As expected, we observed that greater temporal distance is associated with a higher level of granularity in describing negative emotions in the review ($\beta = 0.013$, S.E. = 0.001, $t = 13.56$, $p = .000$, 95% CI = [0.011, 0.015]).

The Effect of Temporal Distance on Review Rating. Given the link between granularity in describing negative emotions and successful coping, and the effect observed above showing that greater temporal distance is associated with higher negative emotional granularity, we have predicted greater temporal distance to be associated with higher review ratings, especially when the overall experience is negative (i.e., when coping is more relevant). To test this, we estimated Model 2.3 to predict review rating with temporal distance, sentiment, and the temporal distance \times sentiment interaction, while controlling the same control variables that were included in Models 2.1 and 2.2.

The full results of this regression are also presented in Table 3. A more positive review sentiment ($\beta = 0.139$, S.E. = 0.001, $t = 151.55$, $p = .000$, 95% CI = [0.137, 0.141]) and greater temporal distance ($\beta = 0.027$, S.E. = 0.001, $t = 35.67$, $p = .000$, 95% CI = [0.025, 0.028]) were both associated with more positive ratings. However, importantly, we also observed a temporal distance \times review sentiment interaction ($\beta = -0.028$, S.E. = 0.001, $t = -36.63$, $p = .000$, 95% CI = [-0.030, -0.027]). When sentiment was negative (i.e., the overall consumer experience was

negative, and coping was more relevant), greater temporal distance was associated with a more positive rating of the business ($\beta = 0.055$, S.E. = 0.001, $t = 51.09$, $p = .000$, 95% CI = [0.053, 0.057]). Interestingly, however, when sentiment was positive, a greater temporal distance was not associated with the review rating ($\beta = -0.002$, S.E. = 0.011, $t = -1.40$, $p = .161$, 95% CI = [-0.004, 0.001]), which is consistent with our coping-based argument of the effect of temporal distance: when the overall experience is positive and thus, coping is not relevant, an increase in temporal distance does not contribute to more positive ratings.

The Mediating Effect of Negative Granularity. As argued, higher granularity in describing negative emotions should enable coping when coping is relevant (i.e., when the overall experience is negative), which suggests that negative granularity should mediate the temporal distance \times sentiment moderation effect on review ratings. Therefore, we conducted a moderated mediation analysis using the Process Macro in Python (Process Model #14). In this model, we included review rating as the predicted variable, temporal distance as the predictor, negative granularity as the mediator, and sentiment as the moderator of the link between the mediator (negative granularity) and the predicted variable (rating), while controlling for all the control variables in Model 2.3. The moderated mediation index did not include zero (index = -.0012, 95% CI [-.0014, -.001]), which indicates a significant moderated mediation. As expected, the indirect effect of temporal distance on review rating through negative granularity (mediator) was stronger when sentiment was negative (effect = .003, 95% CI [.003, .004]) than when it was positive (effect = .001, 95% CI [.001, .001]). This moderated mediation pattern is consistent with the notion that temporal distance is associated with an increased granularity in describing negative emotions, which then contributes to more positive ratings when coping is relevant (i.e., when sentiment, which measures the negativity of the overall experience, is negative).

Discussion

Study 2 demonstrated that the temporal distance between the consumption experience and the writing of the review, as a situational factor that reduces the viscosity of the experienced emotions, is associated with higher granularity in describing negative emotions. Importantly, we also observed the consequences of this increased granularity on the rating assigned to the business through a moderated mediation analysis. We observed that when the overall experience is negative, and coping is relevant, greater temporal distance is associated with more positive ratings, and this effect is mediated by granularity in describing negative emotions. On the other hand, when the experience is positive, and coping is not relevant, temporal distance does not improve ratings. These results are important as they demonstrate that individuals' granularity in describing their negative emotions may be impacted by situational factors, with implications for coping with negative experiences and review ratings.

Furthermore, study 2 replicated the result of study 1 by showing that particularly when the overall experience is negative, higher granularity in describing negative emotions in the review text is associated with a more positive rating of the business.

GENERAL DISCUSSION

Studies show that over 90% of consumers use online reviews as a source of information to guide their purchases (Forbes 2022), and even a single review rating has a strong effect on consumers' purchase likelihood (Vana and Lambrecht 2021). These facts make consumers' decisions on how to rate a business post-consumption an important one to study. We studied

consumer's online review rating decisions from the perspective of consumer coping, and by considering the degree of granularity with which reviewers describe their negative emotions in their reviews. Although the notion of emotional granularity has received considerable attention in the psychology domain over the past three decades (e.g., Barrett and Gross 2001; Hoemann et al. 2021), to date, research in marketing and consumer behavior has not investigated its implications for consumer decision making.

Our research contributes to the online review literature by (1) providing correlational evidence of the impact of granularity in negative emotions, as a catalyst for coping, in shaping online review ratings, (2) elucidating how consumers' emotional granularity evolves as they write more online reviews, and (3) identifying temporal distance as a situation factor that impacts granularity, with consequences for review ratings. We found several novel effects. First, in line with previous research which shows that higher granularity in describing negative emotions is associated with coping success, we observed that particularly when the overall consumption experience is negative, higher granularity in describing negative emotions is associated with a more positive rating of the business. We observed this effect at two levels. First, at the situation level, the results showed that a higher degree of granularity in describing negative emotions in a specific review is associated with a more positive rating of the business, especially if the overall consumption experience described in the review is negative. Second, at the trait level, reviewers who have a propensity to describe their negative emotions more granularly across their reviews on the platform provide more positive ratings, and this effect is stronger for negative consumption experiences.

Second, we observed that as reviewers progressively write more reviews on the platform, they describe their negative emotions more granularly in their reviews. This result is consistent

with previous research in psychology which views emotional granularity as an ability or skill, and suggests that the practice of writing reviews may help improve consumers' ability to describe their negative emotions more granularly (Erbaş et al. 2018; Hoemann et al. 2021), with consequences for consumer ratings. Namely, as consumers progressively write more reviews, their reviews become more positive, and this effect is stronger for negative consumption experiences, for which coping is most relevant. Although earlier research has investigated the effect of factors such as platform-defined expertise (Nguyen et al. 2020; Tamaddoni et al. 2023; Zhang et al. 2020) and self-selection of prolific versus non-prolific reviewers (Schoenmueller, Netzer, and Stahl 2020) on review ratings, to the best of our knowledge, the progression of reviewers' reviewing history as a predictor of review rating has not been investigated.

Finally, we observed that the granularity with which consumers describe their negative emotions in their reviews is higher when there is greater temporal distance between receiving the service and writing their review. Consistent with the popular saying that "time heals all wounds," we further observed that temporal distance increases the positivity of review rating, although this effect is moderated by the valence of the experience described in the review: the increased positivity holds only for negative consumption experiences, for which coping is relevant. Importantly, this moderation was mediated by negative emotional granularity. While Huang et al. (2016) have earlier demonstrated a positive link between temporal distance and review ratings, our results extend their findings by studying the effect through the lens of emotional granularity and coping success, and uncovering an important boundary condition of the effect: the effect holds only when the experience is negative (and therefore, coping is relevant).

Our research also contributes to the line of research on the role of feelings and emotions in consumer decision making, which has been studied extensively (e.g., Avnet, Pham, Stephen

2012; Cohen, Pham, and Andrade 2018; Chang and Hung 2018; Faraji-Rad and Pham 2017). An important subset of this line of research does focus on the role of specific types of emotions in decision making (Allard and White 2015; Cavanaugh et al. 2015; Raghunathan and Pham 1999; Raghunathan et al. 2006). However, previous research on consumer decision making has not investigated whether consumers' propensity to differentiate between their emotions also influences their decisions. This is despite the fact that research in psychology over the past decades has provided evidence of the impact of negative emotional granularity on decision making, health, and well-being (Kashdan et al. 2010; Kashdan et al. 2015; Hoemann et al. 2021). We introduced the notion of emotional granularity to the consumer behavior and marketing literatures and developed a novel deep-learning-based method to measure the emotional granularity in language by using unstructured textual data from consumers. Several novel marketing-related effects were tested based on prior research on the association between negative emotional granularity and coping success. Future research could investigate the impact of emotional granularity in domains other than the one we focused on in our research. For example, how does emotional granularity affect interpersonal influence, the likelihood of sharing online content, or trust in misinformation?

Future research could also explore the role of granularity in positive emotions in consumer decisions. The focus of our research was on negative granularity because coping is relevant only for negative emotions and also because previous research on emotional granularity has consistently observed the effects of emotional granularity in negative emotions on decision outcomes (see Hoemann et al. 2021 for a review). We observed that granularity in positive emotions reduces the positivity of review ratings. Although not a priori predicted, we find this observation to be consistent with the feeling-as-information theory (Pham 1998; Schwarz 2012).

Reviewers who explain their positive emotions more granularly are possibly more likely to consider the representativeness and relevance of their feelings for the decision at hand, which is their rating of the business (Pham 1998). This may reduce the total sum impact of feelings on their decision because some of these feelings may be judged to be non-representative and/or non-relevant to the decision.

Our research also contributes to the broader research on emotional granularity in psychology by developing a deep-learning-based approach that enables the measurement of the construct at the situation level. Specifically, it is the first to demonstrate that situation-level differences in describing negative emotions related to unpleasant experiences predict successful coping with these experiences. Thus, mere *possession of the skills* to understand emotions granularly may not be enough for one to successfully cope with unpleasant situations; it is also important to *use* these skills *within each situation* to review, process, and granularly describe one's negative emotions stemming from that situation to successfully cope with the negative feelings. Therefore, in addition to interventions intended to develop individuals' emotional skills (Brackett et al. 2012; Kircanski, Lieberman, and Craske 2012), interventions that remind or 'nudge' people to *use* these learned skills may also help individuals to cope with negative experiences of interest. Future research may, for example, benefit from investigating the role of effort and cognitive engagement in how granularly people describe their emotions (Barrett and Gross 2001). In addition, because most prior evidence on the effect of emotional granularity on coping comes from behavioral lab studies (e.g., Barrett et al. 2001), the magnitude of the impact of emotional granularity in real-world settings was not empirically tested. Our research tests the effect in a real-world service context and demonstrates that this magnitude is significant. While even marginal increases in review ratings have been shown to influence business outcomes

(Proserpio and Zervas 2017), we observed that negative emotional granularity was associated with about a 0.4 difference in ratings of reviews with negative sentiment.

Furthermore, the marketing field's interest in utilizing the richness of unstructured textual data to study consumer behavior has increased in the past few years (Berger et al. 2019). Researchers have used various methodological approaches in these studies, including manual coding, bag of words, and topic modeling (Berger and Packard 2022). Our research is among the few in an emerging line of research (e.g., Boghrati and Berger 2023) that uses the advances in NLP and deep learning methods to study textual consumer-generated data. Methodologically, our research is novel as it acknowledges the ability of LLMs such as BERT to code the context of each word, rather than coding a representation of the word from a training corpus, as is done by classic word embedding models such as Word2Vec and GloVe. Future research may benefit from studying the application and implications of our methodological approach in other areas of marketing (e.g., coding the context surrounding brand names instead of emotion labels, as we have done).

Finally, our research has downstream implications for the emerging research on psychological targeting and profiling (Abdurahman et al. 2023; Bhatia and Walasek 2023; Matz et al. 2016, 2017, 2020; Matz and Netzer 2017; Neumann, Tucker, and Whitefield 2019). In our data, we observed that the effects of negative emotional granularity are parallel whether the construct is measured as a trait-level variable or a situation-level one. Individuals' emotional competency is a significant predictor of their development (e.g., Izard et al. 2001), decision making (e.g., Shiv et al. 2005), professional success (e.g., Pirsoul et al. 2023), and health and well-being (Starr et al. 2019; Tomko et al. 2015), where emotional granularity has long been considered as an important component of emotional competency (Hoemann et al. 2021). This

suggests that our deep learning-based method, which measures emotional granularity unobtrusively, by merely analyzing what people say, may be applied to predict outcomes that have been shown to correlate with expertise in emotions (e.g., job candidates' success in coping with work-related stress). Future research is needed to test this effect and to understand the privacy implications of such profiling (Matz et al. 2020).

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