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ORIGINAL ARTICLE

The social process of coping with work-related stressors online: A machine learning and interpretive data science approach

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Abstract

People are increasingly turning to social media and online forums like Reddit to cope with work-related concerns. Previous research suggests that how others respond can be an important determinant of the sharer's affective and well-being outcomes. However, less is known about whether and how cues embedded in the content of what is shared can shape the type of responses that one receives from others, obscuring the joint and interactive role that both the sharer and listener may play in influencing the sharer's outcomes. In this study, we develop theory to advance our understanding of online coping with an explicitly social focus using computational grounded theorizing and machine learning (ML) techniques applied to a large corpus of work-related conversations on Reddit. Specifically, our theoretical model sheds light on the dynamics of the online social coping process related to the domain of work. We show that how sharers and listeners interact and react to one another depends on the content of stressors shared, the social coping behaviors used when sharing, and whether the sharer and listener belong to the same occupational context. We contribute to the social coping literature in three ways. First, we clarify how social actors respond to cues embedded in the social coping attempt. Second, we examine the moderating role that such responses play in shaping sharer outcomes. Finally, we extend theory on social coping with work-related stressors to the online domain. Taken together, this research highlights the importance of the dynamic interplay between sharer and listener in the context of online social coping.

KEYWORDS
computational grounded theorizing, machine learning, social coping, social media, social support, stressor

1 | INTRODUCTION

> "The nurses are pissed, management is overwhelmed and everything is fucked"
>
> —Anonymous Reddit user (ID 85327)

The workplace generates a great deal of stress for many people. According to a survey of US employees, 66% identified the work domain as a significant source of stress, more than any other source (American Psychological Association, 2021). Employees can cope with work-related stressors by sharing and discussing them with others (Baer et al., 2018; Baranik et al., 2017; Knipfer & Kump, 2022), and, mirroring broader trends in computer-mediated communication, employees are increasingly turning to social media as a way to cope (Lee, 2020; Miles & Mangold, 2014). This is especially true during the COVID-19 pandemic, which has exacerbated common work-related stressors including job insecurity (Lin et al., 2021), heavy workloads (Shao et al., 2021), and work-family conflict (Vaziri et al., 2020).

Social coping, or relying on others to help manage demands that one appraises as taxing or exceeding resources, can assume various forms (Carver et al., 1989; Lazarus & Folkman, 1984). Two of the most relevant forms to online work-related conversations are: (a) informational support-seeking, where one seeks advice or information from others (Carver et al., 1989; House et al., 1985) and (b) emotional social sharing, where one expresses negative emotions to others in an attempt to vent, or "offload" the emotion, or to garner emotional support (Brown et al., 2005; Carver et al., 1989; Rimé, 2009; Rosen et al., 2021). Although these literatures have produced a number of important insights, they tend to focus considerably more on the focal person engaging in coping than on the role that the social context may play (Revenson & Lepore, 2012). However, organizational research has recently started to incorporate theoretical nuance into this process by seeking to understand how the listener's approach to the interaction influences outcomes for the person engaging in coping. For example, Behfar et al. (2020) found that responding to emotional venting with a "challenging" response can improve problem solving outcomes for the person engaging in venting. In another study, employees engaging in "unfairness talk" about their supervisors were more likely to experience hope, and less likely to experience anger when coworkers employed a "reframing" response (Baer et al., 2018).

These kinds of models, which explicitly account for the role of the social environment, may help to clarify mixed findings in the literature around the effectiveness of certain coping behaviors. One limitation of these studies, however, is that they tend to treat the response from the listener as exogenous to the social interaction, potentially obscuring how the interaction itself might shape the response, and highlighting how the listener *should* respond but not necessarily how they *do* respond. In other words, we argue that the listener's response is likely influenced by cues in the conversation, such as the nature of the stressor that is prompting the need to cope and the type of social coping behavior employed. Framing this process more as a dynamic conversation would enable us to explore how the listener responds to these cues from the sharer and how the joint effect of both the sharer's social coping behavior and the listener responses relate to the sharer's outcomes. We construe social coping as a process whereby one party (hereafter the "sharer") shares information about work-related stressors and attempts to cope with them, another party (hereafter the "listener") responds with a comment, and this ultimately relates to the affective outcomes of the sharer. This approach could yield novel theoretical insights about the nature of these conversations, potentially shedding light on interventions to improve them.

Additionally, much of the previous research on social coping in the organizational literature takes a narrower, more isolated approach to the role of stressors (e.g., difficult customers; McCance et al., 2013) and responses from interaction partners (e.g., reframing; Baer et al., 2018), which limits our ability to theoretically integrate findings that assess these relationships across studies. Stress and coping theorists emphasize that specific coping behaviors can help people navigate specific situations that people appraise as threatening (Chronister & Chan, 2007; Krohne, 2001). Thus, to better understand this process through an interactive lens, we believe that a more contextual and inductive account of stressors and responses is necessary.

Finally, most organizational research on social coping involves face-to-face interactions with others in the workplace or with personal confidants outside of the workplace. These pre-existing relationships feature social norms that dictate many aspects of the social coping process, from the candor with which sharers may discuss the details of their work experience to the emotions they convey and the type of response the listener employs (Behfar et al., 2020). With the ubiquity of social media, sharing one's views and experiences is increasingly less confined to interaction partners with whom one has an existing relationship (Choi & Toma, 2014). This reality presents an opportunity to study how people seek and provide support with anonymous strangers in a virtual setting, where authentic emotions and concerns are more readily expressed due to a reduced fear of reprisals (Corritore et al., 2020; Kafetsios et al., 2017). Thus, we answer recent calls in the literature suggesting that, "one particularly promising path for expanding the scope of social support research would be to investigate the role that social network use (e.g., LinkedIn and Facebook) plays in providing social support in a work context or to individuals seeking support for work issues" (Jolly et al., 2021, p. 244).

We address these oversights in the social coping literature by using a grounded theorizing approach (Strauss & Corbin, 1998) to develop theory of the work-related online social coping process, using interpretive data science (Nelson, 2020). We apply several machine learning (ML) and text analysis techniques to code elements of conversations between users on Reddit, a popular social networking site where people share and discuss their thoughts, emotions, and experiences. Through an inductive analysis of these rich textual data, we develop theory to enable a deeper understanding of the online social coping process and to spur additional organizational scholarship on this important phenomenon.

Our analysis identified a number of theoretically-meaningful patterns that we formulated into testable propositions. We found that listeners seem to respond to two different independent cues embedded in the sharer's post: the work-related stressors described and the approach the sharer to cope with those stressors. For example, the type of strategy listeners employ, like providing information or socioemotional support, may be influenced by the occupational specificity of the stressor, the degree of information-seeking conveyed in the post, the degree of certainty or motivational state conveyed by the expression of discrete emotions, and whether the sharer and listener come from the same occupational category. In addition, we found that the sharer's affective reactions to this conversation depend on the interaction between the specific coping behaviors they employed and the responses listeners offered. For example, we found that the deleterious effect of expressing anger is exacerbated when the listener provides informational support and the adaptive effect of expressing fear is enhanced when the listener offers a new perspective that helps reframe the sharer's problem.

Taken together, our study makes three theoretical contributions. First, we contribute to theory on the enactment of support in a social coping context by providing a more integrated and comprehensive account of the cues that listeners use in formulating their response to sharers. Second, we contribute to the nascent body of research on the important role that listener responses play in modulating the effectiveness of social coping behaviors. Taken together with insights on the effects of social coping behaviors on listener responses, this highlights the dual roles that social coping behaviors play—to help the sharer cope with the stressor directly and to marshal resources from others—and we show how one can enhance, or offset, the effects of the other. Third, we extend theory on work-related social coping to the

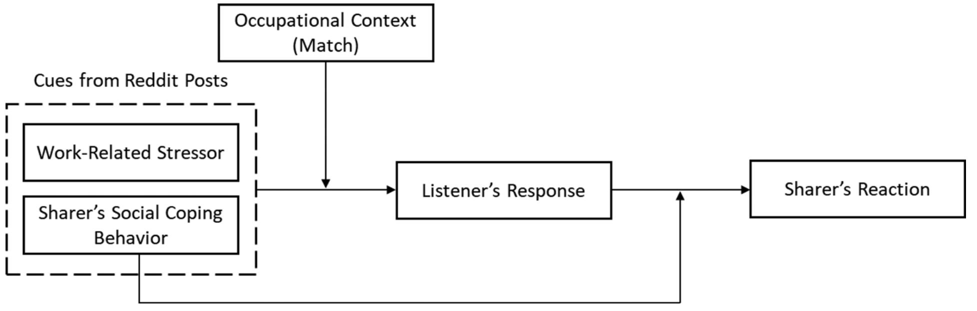

FIGURE 1 Conceptual model of online social coping process

online domain, where people interact with weak ties or even total strangers as they seek to cope with work-related stress.

1.1 | Developing theory on the social nature of online coping

We rely on a variation of the classic grounded theory methodology by Glaser and Strauss (1967), sometimes referred to as "grounded theorizing" (Holton, 2018). In grounded theorizing, a theory-neutral, clean-slate start is considered to be impossible and instead adopting existing theoretical frameworks informed by extant research is prescribed (Partington, 2002). We integrate the Transactional Model of Stress (Lazarus & Folkman, 1984) with extant research on social support (see Bavik et al., 2020 for a review) to inform a model of the online social coping process (see Figure 1).

Applied to the online context, these theories suggest that there are three primary components of online social coping in rough temporal order. First, someone decides to write a post about a work-related stressor that is appraised as threatening or exceeding available resources. The post typically includes both a description of the situation/event and evidence for the way in which the sharer is using social media to cope with it (e.g., to solicit information or to vent negative emotions). Second, listeners respond to the post. Finally, the sharer experiences some affective reaction to this conversation, which is reflected in the sharer's subsequent reactions to the listener's response. Figure 1 shows the conceptual model of this process, which guides our research questions and subsequent analyses.

1.2 | Work-related stressors and social coping behaviors

Work-related stressors refer to demands or events requiring people to adjust their usual behavior patterns related to work (Frone et al., 1995; Sonnentag, 2018) such as work pressure, lack of autonomy, and role ambiguity (Frone et al., 1995). When confronted with stressors that people appraise as taxing or threatening, they can employ several coping behaviors to reduce the adverse effects of those stressors (Lazarus & Folkman, 1984). Many of these coping behaviors can be employed when one is alone, however, some coping behaviors inherently require the aid of someone else as a resource, referred to as social coping (Carver et al., 1989). As social creatures, people are likely to turn to their social environment during difficult times, as exemplified by the well-known "tend and befriend theory" (Taylor, 2011). For example, Yang et al. (2021) found that during the COVID-19 pandemic, employees experiencing stressors of job insecurity or remote work were more likely to reach out to dormant ties.

We focus on two social coping behaviors that have been investigated in the literature: (a) *informational support seeking* and (b) *emotional social sharing*. Informational support seeking is a problem-focused coping behavior that is commonly used on social media (Frison & Eggermont, 2015; Wang et al., 2015) and refers to asking for information or advice from others, which can be used to alter one's behaviors to accomplish goals and solve problems (Taylor et al., 2004). Emotional social sharing, whereby individuals communicate openly with one another regarding the circumstances surrounding the emotion-evoking event, and their own feelings and emotions (Rimé, 2009), is another common form of social coping, and one that is also often used on social media (Vermeulen et al., 2018; Wang et al., 2015). This is an emotion-focused coping behavior because the intent is typically either to garner sympathy or comfort from the social interaction or to reduce the experience of the emotion by venting it to others (Brown et al., 2005). Although most often associated with expressions of anger, emotional social sharing can include other emotions as well (Brans et al., 2014; Luo et al., 2020).

1.3 | Listener responses as a function of sharer cues

Sharing stressful work situations with others can invite a range of responses and a number of different models in the literature have attempted to capture these responses. For example, House and colleagues developed a model of social support, which includes emotional, informational, appraisal, and instrumental support (House et al., 1988). Nils and Rimé (2012) focused on a socio-affective (empathic) mode and a cognitive (reframing) mode as possible responses to the shared emotion of others. Some conceptualizations also recognize that the response may not always be positive or supportive, such as Barbee and Cunningham's taxonomy (1995), which also features dismissing or avoiding the sharer as key dimensions. Despite this rich body of research on the ways in which people respond to those in need, less is known about the role that the sharer plays in garnering these responses. The majority of the research in this area tends to treat social support as exogenous and assumes that the sharer is simply a passive recipient of support (Feeney & Collins, 2015; Forest et al., 2021). However, it is likely that the content of the sharer's message plays a role in how the listener responds. Recent theoretical advances in social support suggest that the type of support offered is a function of both the "life adversity" of the recipient and the recipient's response to that life adversity (Feeney & Collins, 2015), which is conceptually similar to work-related stressors and social coping behaviors, respectively. Drawing from this, we posit that the nature of the work-related stressor and the type of social coping behavior employed may be cues that relate to how the listener responds.

A few studies have investigated this proposition. First, there is some work on how social support is provisioned on the basis of sharer cues, largely among confidants like romantic couples, families, and friends. Some of this work focuses on how the nature of the stressor (Horowitz et al., 2001; Lindorff, 2005) or the social coping behavior (Cutrona et al., 2007; Horowitz et al., 2001) relates to the type of support received. Although useful, these studies produce a fragmented picture of how listeners respond to sharer cues as they tend to limit social support behaviors to a few broad categories, like informational vs. emotional support, and they very rarely include cues related to the stressors and social coping behaviors in the same model (see Horowitz et al., 2001; Study 2 for an exception). This obscures a broader theoretical understanding of the myriad ways that listeners respond to these different sets of cues, which are likely present at the same time in the social interaction. In addition, these studies tend to focus on in-person interactions with others, which may overlook subtle differences in how listeners respond online. For example, research shows that greater social distance between the parties affects the type of support offered (Rim & Summerville, 2014). Finally, almost no research has examined these relationships in the work context (see Lindorff, 2005 for a notable exception).

A second body of work has investigated how listeners respond to support-seeking communications in online forums. Some of the research in this domain has examined how listeners respond to stressor and social coping behavior cues embedded in the sharer's post (e.g., Pan et al., 2018; Wang et al., 2015). However, these studies tend to focus on a few broad types of social coping and/or a single specific type of listener response (e.g., Pan et al., 2018), with some operationalizing support as simply liking or re-sharing the help-seeking post (Luo et al., 2020). In addition, many of these studies gather data from online forums dedicated to specific issues, like certain health problems (e.g., Rains et al., 2015) or addictions (e.g., Liu et al., 2017). The nature of sharing and responding in these forums may be different than what occurs on Reddit, where people likely discuss a much broader set of interests and where the participants may be less aligned on any given topic. Despite the importance of employee online complaints in organizational research (Miles &

Mangold, 2014), we know very little about what drives listener responses to these online discussions of work-related problems.

> *Research Question 1*: How do the cues related to (a) different types of work-related stressors and (b) social coping behaviors relate to the types of responses received?

1.4 | The importance of who responds

Much of the preceding discussion implies that listeners may try to infer the needs, goals, or preferences of sharers based on the cues related to the stressor and social coping behaviors, which influence how they will respond. The ability and motivation of the listener to make those inferences and respond in specific ways, however, likely differs as a function of the shared perspective and understanding of the stressor context between the two parties. As such, we also investigate the role of the occupational context match, or the degree to which the sharer and listener work in a similar occupational context, as a proxy for this shared understanding.

Typically, sharers choose the partners with whom they will seek information or express their negative emotions, with research suggesting that sharers choose listeners with whom they are more closely attached and interact more frequently for support (Kammrath et al., 2020). They also tend to seek out listeners who are more supportive and who are viewed as having relevant expertise (Behfar et al., 2020). However, online social coping drastically reduces this ability to choose one's interaction partner. Particularly in forums like Reddit, which are relatively anonymous and open to anyone who is a member of the site, sharers have access to a diverse pool of listeners; thus, even when they share in a more specialized subreddit, they cannot ensure they will receive response from a supportive listener with relevant expertise. This presents an opportunity to explore how people with more dissimilar occupational backgrounds may respond to the cues embedded in the sharer's post differently than those from more similar backgrounds.

There are several possibilities regarding the moderating role of occupational context match. Social identity plays an important role in determining helping behavior (e.g., Levine et al., 2005) and people tend to experience more empathy in response to the stressful events of ingroup members and more schadenfreude for the problems of outgroup members (Cikara et al., 2011). Similarly, listeners from the same occupational context may have more nuanced insight about certain problems faced, which may influence the type of response they give relative to someone from a different occupational context. Conversely, as suggested by the advantages of knowledge dissimilarity between actors in social capital research (Ter Wal et al., 2016), listeners from different occupational contexts may see the problem from a different or fresh perspective and formulate high-quality support. As such, we aim to identify the role that occupational context match plays in influencing how listeners respond to the cues in the sharer's post.

> *Research Question 2*: Does the occupational context match between the sharer and listenermoderate how listeners respond to (a) the sharer's work-related stressors and (b) social coping behaviors?

1.5 | Sharer's subsequent reactions

The literature on social coping has produced mixed findings in terms of the effect of specific coping behaviors on affect and well-being. For example, research suggests that informational support seeking is generally associated with adaptive outcomes in the workplace (e.g., Nifadkar et al., 2019). Meanwhile, the findings for emotional social sharing are more mixed, but many studies suggest that it exacerbates strain and inhibits emotional recovery for employees (Baer et al., 2018; Brown et al., 2005; Bushman et al., 2001; Day & Livingstone, 2001; see McCance et al., 2013 for a notable exception). Similarly, using a combined measure of informational and emotional social coping, Kim et al. (2006) found conflicting results regarding the success of coping across different populations. To reconcile inconsistent findings in this literature, recent research has begun to investigate the active role of the listener in this process.

Empirical research and theory in the social support literature suggests that the effectiveness of social support from listeners depends on its fit with the needs or goals of the person receiving support. For instance, Horowitz et al. (2001) argued that various forms of listener responses were most effective when they matched the coping goal or the problems of the sharer. Specifically, they found that sharers reported the highest satisfaction when they shared an action-related problem (i.e., a performance failure) and the listener provided actionable plans in response, or when sharers described an emotionally distressing event (i.e., a romantic breakup) and the listener demonstrated understanding and empathy. However, in another study, coworkers displaying understanding and validation of the sharer's affect-laden thoughts about an unfair supervisor related to more negative emotions, whereas cognitively reframing the unfairness situation reduced anger (Baer et al., 2018). In a similar vein, both experimental and qualitative research has shown that challenging the sharer's initial premise provided new insight and led to better responses and outcomes for the sharer in not only face-to-face (Behfar et al., 2020) but also online settings (Meurer et al., 2022).

These studies show that listener responses matter with regard to how social coping behaviors relate to the affective outcomes of sharers. However, there is conflicting evidence about the nature of the effects that listener responses have. In part, this may be due to the fact that these studies are often conducted on only one or a few types of listener responses (e.g., instrumental vs. emotional) and in the context of a single stressor (e.g., supervisor unfairness), which limits a more integrated theoretical understanding of how listener responses play a role in this process. This motivates us to explore the effect of several listener responses on the relationship between social coping behaviors and sharer affective reactions, while also accounting for the broader context of work-related stressors.

> *Research Question 3*: How do listener responses and their interactions with social coping behaviors relate to the sharer's affective reaction?

2 | METHOD

To answer our research questions, we used computational grounded theorizing—a variation of the classic grounded theory methodology (Holton, 2018). In grounded theorizing, scholars adopt a theoretical framework that informs their research because they do not consider a theory-neutral state to be possible (Partington, 2002). We used the theory-derived model illustrated in Figure 1 to inform our approach to analyzing the data. In particular, we used this model to guide the types of categories we coded in the data (e.g., the specific work-related stressors, social coping behaviors, and listener responses), using computational methods to quantify the unstructured text into several variables (Nelson, 2020). Next, we used this model to determine the specific quantitative relationships between those variables that we would analyze and subsequently interpret using an inductive approach. These patterns of quantitative relationships between key variables in our model represent what Puranam and colleagues call "stylized facts," which are important building blocks for theory-building in quantitative induction (Puranam et al., 2018). Below, we explain our methods, starting with the data collection and then the process of quantifying the data into various categories.

2.1 | Data collection

We collected data from the online community, Reddit. People use Reddit to post content and interact with others in "subreddits," which operate like message forums organized around specific interests or topics (e.g., the "working-moms" subreddit). When others come across these posts, they can choose to respond to them, or to the responses of others, which often creates a series of distinct conversations that operate in parallel under the original post. Unlike other social media platforms like Twitter, which restricts the number of characters that can be used in a single post

(280), Reddit's character limit is high (40,000), which tends to encourage rich discussions between the participants. In addition, Reddit users often contribute to the discussion under aliases and do not need to send and accept "friend requests" with other users to engage with one another (in contrast to the usual practice in other social networks like Facebook). These features mean that the discussions on Reddit are often among anonymous strangers who only share some interest in the topics discussed.

We collected three datasets from Reddit using the official Reddit application programming interface (API). Our first dataset, "Dataset 1" consisted of conversations from January 2020 to January 2022, including the original posts (hereafter, "the posts") and responses to them (hereafter, "the responses") that were related to work and workers' experiences. The API does not allow for wide-scale text scraping of the website and limits keyword searches to specific subreddits. We decided to search subreddits that functioned as general discussion boards (e.g., askreddit), specialized support groups (e.g., workingmoms), work-related subreddits (e.g., work, jobs), advice-centered subreddits (e.g., careerguidance), subreddits in which people might vent about work (e.g., antiwork), or in which users vent in general (e.g., vent), as well as occupation-specific subreddits (e.g., teachers, nursing).

We searched these subreddits for posts and responses containing the keywords, "work," "job," "office," "position," "laid," "layoff," "furlough," "employ," "manager," "boss," "colleague," OR "career." Our search was not case sensitive and also included other words that might contain these keywords (e.g., "worker" contains the word "work"). To complete the keyword list, we followed an iterative process that involved brainstorming an initial set of keywords, searching for posts that included these initial keywords, and then, reading random samples of these posts with the goal of finding more potential keywords that can be included in the keyword list. Given that our study aims to understand the interactive process of online social coping, we only kept conversations that had at least one response. This step resulted in a dataset (hereafter, Dataset 1) with 21,990 conversations, including 313,524 posts and responses, by 102,279 unique individuals (hereafter, the Redditors) in 18 subreddits (see Table S1 in the online supplementary document for the full list).

Dataset 2 consists of the activity report of Redditors whose posts were represented in Dataset 1. These data show in which subreddits a Redditor was active (e.g., Redditor *X* was active in the "nursing" and "workingmom" subreddits). Because it reflects the Redditors' interests, Dataset 2, along with Dataset 3 introduced next, helped us to categorize the Redditors' occupational contexts. Dataset 3 consists of all posts by the Redditors represented in Dataset 1, posted in any subreddit about any topic. Before analyzing the data, we first followed Hickman et al.'s (2022) recommendations and pre-processed our textual data. In particular, we converted the data to lowercase, removed stop words (common words, such as "a," "the," "is," "are"), posts by bots, words that were repeated in the data fewer than five times (usually typos or proper nouns), and posts with fewer than 10 words.

2.2 | Overview of ML methods used

To translate the unstructured textual data into meaningful constructs, we used interpretive data science, which is a combination of qualitative analysis of the text and ML techniques. In this process, we used three ML techniques, including unsupervised and supervised learning, and word embedding. We first give a high-level overview of these ML techniques before explaining how they were employed to operationalize the specific constructs in our study. The basic steps of these methods are summarized in Figure 2. ML code is available at this Open Science Framework (OSF) link: https://osf.io/eytjr/?view_only=6fc0dc7328464540ae7aa963f3133f9e.

2.3 | Unsupervised machine learning

We used topic modeling, an unsupervised ML technique, to understand the nature of the work-related stressors shared on Reddit. Unlike supervised learning methods that assume a predefined set of categories into which data are

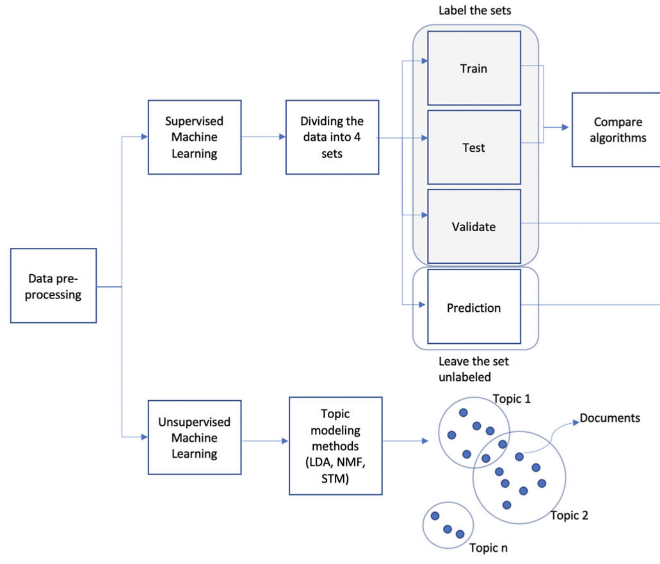

FIGURE 2 Data analysis processes: supervised machine learning and unsupervised machine learning

classified, topic modeling is an unsupervised clustering method in ML used to find latent topics in unstructured textual data (DiMaggio et al., 2013; Mohr & Bogdanov, 2013). These topics often represent the underlying meanings of the group of texts that belong to that topic. As such, topic modeling is a dimension reduction method similar to principal component analysis (PCA). In topic modeling, similar to PCA, the number of topics need to be decided in advance. We compared the performance of three topic modeling methods, Latent Dirichlet Allocation (LDA; Blei et al., 2003), Non-Negative Matrix Factorization (NMF; Lee & Seung, 1999), and Structural Topic Modeling (STM; Roberts et al., 2019) to select the model that performed best (for technical details please see Appendix A).

2.4 | Supervised machine learning

To identify social coping behaviors, listener responses, and redditors' occupations we used supervised ML. The goal of supervised ML is to train an algorithm using a labeled sample to accurately label (categorize) the remaining unlabeled data (prediction sample). Before applying the trained algorithm to the prediction sample, one needs to ensure the algorithm is reliable and valid. To classify our data into the categories of interest (our study constructs), we first randomly divided data into two parts: (a) the ground truth sample, which includes a small random sample of Reddit posts that we manually label through qualitative coding into the categories of interest, and (b) the prediction sample, which includes the remaining unlabeled data. We used the ground truth sample to train, test, and validate the algorithms, so it must be as precise and accurate as possible (Tay et al., 2021). These categories of interest reflect the constructs in our study. For example, in the case of social coping behaviors, we categorized (labeled) a sample of the data into three labels: Informational Support Seeking, Emotional Social Sharing, and General Opinion/Other.

To create a ground truth sample, we hired research assistants (RAs) and trained them to label the data (details discussed later). The next step was to randomly divide the *ground truth* sample into three parts: *training*, *test*, and *validation* samples. We used the labeled data in the *training* dataset to train and tune multiple ML algorithms and compared and optimized their performance in categorizing (labeling) the data, by applying the trained algorithms to the *test* dataset. The algorithms we used, Naïve Bayes, Random Forest, Support Vector Machine (SVM), and Logistic Regression, are known for classifying textual data (James et al., 2013; Kowsari et al., 2019). We evaluated the performance of the algorithms using precision, recall, and accuracy metrics, which are commonly used to evaluate algorithm performance (Nelson et al., 2021; van Rijsbergen, 1979). Next, we applied the algorithm with the highest level of accuracy and F1 score (the harmonic mean of precision and recall) on the validation sample to ensure the algorithm performs accurately beyond the test sample. This step ensures that the selected algorithm is not simply fine-tuned to either the *training* or *test* datasets, and that the algorithm can accurately label new datasets. Consistency of the accuracy metrics across different algorithms indicates inter-algorithm reliability, which is similar to inter-rater reliability and the algorithms' accuracy in classifying the validation sample indicates their validity (Sajjadiani et al., 2019). After validating the algorithm, we applied it to the unlabeled *prediction* dataset to label the remaining data that we did not manually label into the categories of interest. This process is summarized in Figure 2.

In this study, we specifically used the multi-label classification technique, in which labels are not mutually exclusive. To do so, we converted the labeled dataset into multiple single-labeled datasets to transform the multi-label classification into multiple binary classifications (Brucker et al., 2011; Liu & Tsoumakas, 2020; Tsoumakas & Katakis, 2007).

2.5 | Word embedding

To measure expressed emotions and affective reactions in the posts, we used word embedding to quantify the extent to which a text is similar to certain concepts of interest. In this study we use two types of word embedding models: (1) Word2Vec (Mikolov et al., 2013), which we use to measure how much the texts were similar to certain concepts of interest, and (2) BERT, a deep learning transformer model (BERT; Devlin et al., 2019), which we use to measure basic emotions in the text. The technical details are provided in Appendix A.

2.6 | Identifying work-related original posts

Given that the goal of this study is to understand social coping with work-related stressors, we first needed to identify and delete the posts that were not work-related. We trained the RAs to categorize a random subset of 1000 original posts using a dummy variable indicating whether the post is work-related or not. We then applied supervised ML, as explained above, to categorize the data into work-related and non-work-related posts. This process accurately labeled whether the posts were work-related, as agreement between the manually labeled data and machine labeled data in the validation sample was 98%. Given that the goal of this study is to understand social coping with work-related stressors, we deleted the posts that were not categorized as work-related.

2.7 | Identification and operationalization of constructs

Next, we will introduce each of the main elements of the online conversation that are shown in Figure 1. We will explain how we used ML and qualitative coding techniques to identify and operationalize the constructs within each element and provide evidence of the reliability and validity of these measurement techniques. These methods are summarized in Table 1.

2.8 | Sharer's work-related stressors

To identify the content of the work-related stressors discussed in the posts, we used unsupervised ML to cluster the posts by their overall topic. We ran LDA, NMF, and STM 25 times, starting with a five-topic model, and

TABLE 1 Identification and operationalization of constructs

Conversation elements	ML technique	Ground truth sample	Reliability	Validity	Labeled constructs
Sharer's Work-Related Original Posts	Supervised Machine Learning	Manually labeled posts by RAs	Various algorithms classified data similarly. Accuracy rates reported in Table 4	High accuracy scores and high agreement between human and machine labeling	Work-related
Sharer's Work-Related Stressors	Unsupervised Machine Learning, Topic Modeling	NA	Similar results using STM, NMF, and LDA (inter-rater reliability). Posts are grouped together under the same topic using different methods.	Odd word out and 2 RAs and 3 authors came up with similar titles for the topics	See Table 6 for list of 18 stressors
Sharer's Social Coping Behaviors	Supervised Machine Learning for each category	Manually labeled posts by RAs	Various algorithms classified data similarly. Accuracy rates reported in Table 4	High accuracy scores and high agreement between human and machine labeling	(1) Informational support seeking, (2) Emotional social sharing, (3) General opinion/Other
Sharer's Expressed Emotions in the Original Posts and Reaction Posts	Word Embedding	Training: Google training dataset. Validation sample for shared emotions: 2 RAs independently labeled the same sample of 200 main posts for each emotion and agreed on 145 posts. For reacted emotions 3 RAs independently labeled the same sample of 300 reaction posts for each emotion	Various algorithms (Word2Vec and BERT), LIWC, and RAs classified data relatively similarly. Accuracy rates reported in Table 4	Higher agreement between RAs and ML than between RAs and LIWC	Anger/Disgust, Sadness, Fear, and Satisfaction

(Continues)

TABLE 1 (Continued)

Conversation elements	ML technique	Ground truth sample	Reliability	Validity	Labeled constructs
Listener Responses	Supervised Machine Learning for each category	Manually labeled posts by RAs	Various algorithms classified data similarly. Accuracy rates reported in Table 4	High accuracy scores and high agreement between human and machine labeling	(1) Informational support, (2) Positive socioemotional support, (3) Negative socioemotional support, (4) Opposition, (5) Reciprocal sharing, (6) Reframing
Sharer-Listener Occupational Context Match	Supervised Machine Learning for each category	Manually labeled posts by RAs +Regular Expression search for explicit expression of occupation in Redditors' posts (Dataset 3)	Various algorithms classified data similarly. Accuracy rates reported in Table 4	High accuracy scores and high agreement between human and machine labeling	(1) Healthcare workers, (2) Retail workers, (3) Educators, (4) Food services workers (5) Office/Corporate workers, (6) Other service workers, and (7) Unemployed

subsequently increased the number of topics by one until we got to a 30-topic model. We evaluated the performance of each model by reading the top 20 posts in each topic, paying attention to the top words and the distribution of topics. While all three methods performed similarly and resulted in similar themes (an indicator of the reliability of topic modeling), overall, STM performed better in distinguishing different topics and with fewer topics. Another advantage of STM is that it allows the topics to be correlated. Therefore, we moved forward with an 18-topic STM model. To learn about each topic's empirical theme, each author and two RAs independently read the top 20 posts in each topic and chose a title that represented the overarching stressor theme. There was generally high similarity in the titles we chose for each topic. For example, one person labeled a topic, "poor management of workplace mistreatment," whereas another chose "employer mishandling workplace hostility, violence, and other mistreatment," and another chose "employer mishandling issues related to harassment, violence, or mental health." We labeled this topic, "Mismanagement of Equity, Diversity, and Inclusion (EDI) issues." The agreement between the coders in identifying the core stressor themes in topics demonstrates the validity of the method in accurately grouping conceptually similar posts together.

To further validate the algorithm's ability to cluster similar posts, we took the top ten words that the algorithm identified as best representing each topic and then added a randomly chosen word from another topic, as an odd-word-out (Chang et al., 2009). Two RAs were then asked to identify in each of the 18 groupings which word did not belong to the set of 11 words, without knowing the common conceptual theme. In each of the 18 samples, the odd-word-out was determined correctly, validating the machine's ability to group together words under a common conceptual theme. This process led to the following 18 distinct stressor variables: (1) Career Path Ambiguity, (2) Job Search/Application Ambiguity, (3) Concerns about Viability of Quitting, (4) Resignation/Onboarding Process Ambiguity, (5) HR/Management-Related Issues, (6) Unemployment Assistance Issues, (7) Inadequacy of Compensation and Benefits, (8) Scheduling Mismanagement, (9) Work-Family Conflict, (10) Disrespectful Workplace Environments, (11) Mismanagement of EDI Issues, (12) Workplace Exploitation, (13) Interpersonal Conflict, (14) Essential Work Concerns, (15) Field-Specific Teaching Concerns, (16) Field-Specific Nursing Concerns, (17) Field-Specific Postal Work Concerns, and (18) Retail Worker Concerns. Table 2 shows the topics along with the representative words and a representative post for each topic.

2.9 | Sharer's social coping behaviors

Next, we identified the specific social coping behaviors exhibited by the sharers. To do this, we first started by identifying a broad categorization of social coping behaviors.

2.9.1 | Sharer's Broad Social Coping Behaviors in Original Post

First, the authors each independently read and coded a random sample of the same 50 posts for cues about the motivation for sharing each experience on Reddit. Sometimes these cues were quite obvious, and the sharer explicitly stated the intent (e.g., "I just want to vent" or "I'm looking for some advice"). In other cases, the behavior was more subtle and had to be inferred by the entire context of the post. We then compared our codes and discussed any discrepancies in an effort to reconcile them. Drawing on the coping literature described above, we combined the empirical themes we extracted from the posts and identified two main conceptual categories: (a) seeking informational support through asking for advice, suggestions, or feedback (Informational Support Seeking) and (b) expressing negative emotions about the experience or issue raised (Emotional Social Sharing). In particular, those who engaged in emotional social sharing expressed negative feelings of anger, disgust, sadness, or fear associated with the experience, and appeared to do so either to vent those negative emotions or to solicit emotional support. There were also posts that

TABLE 2 18 topics of work-related stressors with example posts and top 10 words from topic modeling

Topic	Theme description	Example	Word 1	Word 2	Word 3	Word 4	Word 5	Word 6	Word 7	Word 8	Word 9	Word 10
1	Career Path Ambiguity	Plan to be a computer designer after graduating college but I chose physics, can a physics MS be a computer designer after college?… (ID 362255)	degre	bachelor	master	career	pursu	path	research	studi	field	creativ
2	Job Search/ Application Ambiguity	… How's… networking industry is going to be 5 to 6 months from now? What to expect if I am job hunting right now in network engineering field? (ID 89587)	interview	resum	offer	recruit	appli	posit	current	applic	refer	opportun
3	Concerns about Viability of Quitting	30 soon, still at home, single. All I do is worry about work, joblessness, what I'll be doing in 5 years time. Thinking about quitting my job (even during this pandemic) and just explore the country… (ID 59068)	hate	stress	mental	job	depress	quit	miser	anxieti	restaur	stuck
4	Resignation/ Onboarding Process Ambiguity	I just started a 9–12 month contract job about 2 weeks ago… I don't like just waiting to hear what I should do next and wondering if I should even be being paid for this right now. (ID 69197)	notic	train	two	leav	contract	month	resign	three	perman	week

(Continues)

TABLE 2 (Continued)

Topic	Theme description	Example	Word 1	Word 2	Word 3	Word 4	Word 5	Word 6	Word 7	Word 8	Word 9	Word 10
5	HR/Management-Related Issues	First-time manager: How do I establish “authority” with undermining junior-level colleagues who are not on my team?… (ID 362618)	promot	project	team	role	leadership	director	review	titl	task	perform
6	Unemployment Assistance Issues	I filed for unemployment and was approved, but didn’t receive a penny of it. I still have the debit card they sent me… (ID 468095)	claim	unemploy	pua	elig	payment	appeal	file	date	california	submit
7	Inadequacy of Compensa-tion and Benefits	… The question is, last time I was compensated with 17k for a 2 year contract and now only 15k for an additional 4 years. Should I be asking for more? (ID 526926)	pay	bonus	wage	rais	salari	minimum	compens	rate	insur	cost
8	Scheduling Mis-management	… They’ve scheduled me multiple 40 hr weeks as a part time employee. And then just arbitrarily expected me to come in unscheduled and one time I don’t, I’m doing something wrong? What the hell do I do here. (ID 517006)	schedul	Friday	Monday	call	tomorrow	email	text	phone	morn	weekend

(Continues)

TABLE 2 (Continued)

Topic	Theme description	Example	Word 1	Word 2	Word 3	Word 4	Word 5	Word 6	Word 7	Word 8	Word 9	Word 10
9	Work-Family Conflict	I am tired. I feel guilty for being so tired all the time. Being a parent and working is rough… (ID 106910)	husband	daycar	mom	babi	pregnant	matern	daughter	son	childcar	dad
10	Disrespectful Workplace Environ-ments	Just wanna know how long can you pretend to work while being micro managed before it drives you crazy. I am ready to throw my boss into a garbage compactor. (ID 334849)	fuck	shit	ass	mistak	liter	stupid	shitti	hell	bullshit	damn
11	Mismanagement of EDI Issues	My coworker was physically assaulted at work (grabbed and left major bruises on her arm). She is now not allowed to work until the investigation is complete (makes sense to me). But the accused is allowed to work? How is that fair?… (ID 400427)	fire	disabl	accommod	termin	complaint	harass	incid	fmla	warn	disclos

(Continues)

TABLE 2 (Continued)

Topic	Theme description	Example	Word 1	Word 2	Word 3	Word 4	Word 5	Word 6	Word 7	Word 8	Word 9	Word 10
12	Workplace Exploitation	Last year, when my company emailed out a list of the paid holidays for 2021, they designated Friday, dec 24 as the observed Christmas holiday. Today, my specific office sent out its own email changing the rules… staying open Friday and requiring us to work… if you choose not to work you now have to use your own PTO. (ID 356317)	christma	owner	holiday	employe	pto	costco	season	gift	eve	labor
13	Interpersonal Conflict	I am working with a very angry person who screams, throws things and sometimes starts fights with people in the office. Let's call her Karen. Karen regularly makes comments about what you're wearing and interrupts conversations etc… (ID 364410)	shes	woman	cowork	girl	joke	yell	hes	aggress	comment	laugh
14	Essential Work Concerns	How in the hell am I essential?! All I do is make dough for a pizza place. How is that essential?… (ID 5296)	mask	virus	essenti	wear	vaccin	risk	ppe	quarantin	distanc	expos

(Continues)

TABLE 2 (Continued)

Topic	Theme description	Example	Word 1	Word 2	Word 3	Word 4	Word 5	Word 6	Word 7	Word 8	Word 9	Word 10
15	Field-Specific Teaching Concerns	… I have no clue what I'm doing for distance learning. Admin gave me a huge list of digital resources but I'm struggling to figure out how to use them for first graders… (ID 262229)	teacher	student	class	teach	summer	school	classroom	semest	grade	exam
16	Field-Specific Nursing Concerns	Finally decided to get a hospital job and I really want to travel after a year. I really like PCU and was wondering if a PCU nurse can take medsurg travel contracts? (ID 452314)	icu	bedsid	nurs	preceptor	cna	patient	clinic	nicu	medsurg	unit

(Continues)

TABLE 2 (Continued)

Topic	Theme description	Example	Word 1	Word 2	Word 3	Word 4	Word 5	Word 6	Word 7	Word 8	Word 9	Word 10
17	Field-Specific Postal Work Concerns	My only issue is another new policy we.ve instituted where following completion of our route we're forced to go back out and do a second trip of whatever parcels we're thrown in the meantime. I probably wouldn't mind as much if it wasn.t for the awful second trip system don't really enjoy going out with parcels and getting paid for load time and maybe in mileage also just seems like a sneaky way to get by the aim to reduce overtime. (ID 253536)	hang	usps	cca	carrier	packag	offic	clerk	deliv	rout	mail
18	Retail Worker Concerns	As someone who has been working retail for almost a year, nothing frustrates me more than a customer who runs into the store two minutes before closing and spends 1015 minutes shopping. Not allowing customers to enter right before closing won't solve the problem… (ID 133617)	walmart	store	cashier	custom	stock	cart	cap	associ	coach	retail

Words are stemmed. PUA: Pandemic Unemployment Assistance. FMLA: Family and Medical Leave Act. PTO: Paid Time Off. CNA: Certified Nursing Assistant. CCA: City Carrier Assistant.

did not seem to be an attempt to cope with a stressor (e.g., expressing general opinions or sharing news). These were categorized into a separate category called Other. Table 3 shows representative posts for each category.

We trained the RAs to follow the labeling strategy we used and to categorize a random subset of 1,000 original conversation-starting posts into three dummy variables: (1) Informational Support Seeking, and /or (2) Emotional Social Sharing, and (3) Other. This manually labeled sample constitutes the ground truth sample. Next, we applied supervised ML to train, test, and validate the above-mentioned algorithms and find the best performing algorithm in classifying the posts into the categories of interest. Table 4 shows the performance metrics for the data categorization of each algorithm. We then applied the best performing algorithm to categorize the prediction dataset into the categories of interest. This resulted in 9,371 work-related original posts categorized as Informational Support Seeking and/or Emotional Social Sharing.

2.9.2 | Sharer's Discrete Emotions in Original Post

Next, we wanted to further code the posts that contained emotional social sharing by labeling the specific discrete emotions expressed in the post. In particular, we aimed to measure each of the basic negative emotions (i.e., anger, disgust, sadness, and fear; Ekman, 1992, 2000). To do this, we compared the performance of two word-embedding methods: Word2Vec and Bidirectional Encoder Representations from Transformers (BERT). The technical details are presented in Appendix A.

To validate the classifications using Word2Vec and BERT, two RAs each independently coded the same random sample of 200 posts for expressions of anger/disgust,[1] sadness, and fear (coded 1 if it contained the emotion and 0 if it did not). The RAs found this more challenging than simply coding for the presence of emotional social sharing. For example, one Redditor lamented "Why I ask is this verbal abuse, is because I am made to genuinely feel awful throughout my day." (ID 8242). One of our RAs labeled this as anger and the other one labeled it as sadness. Nonetheless, they agreed on 145 of these posts, which we used as our *validation* dataset. We then compared the performance of Word2Vec and BERT with the manual labeling. For this comparison, we dichotomized the Word2Vec output to 1 if the value was positive and 0 otherwise. Table 5 shows the agreements between ML models and the manual labeling. The Word2Vec model outperformed the BERT model, in part because the pre-trained data for fine-tuning the BERT model were derived from Twitter posts (for more details see Appendix A), which differ in length and content from Reddit posts. This demonstrates the importance of the ground truth dataset and the need to validate the results with a ground truth sample relevant to the data being analyzed, in the case of using a pre-trained dataset. Based on these findings, we used the Word2Vec model to measure the emotions reflected in the posts.

2.10 | Listener responses

Next, we wanted to identify the types of responses that listeners employ when commenting on the original post of a sharer. To do this, the authors first read and qualitatively coded a random sample of 50 responses. Similar to what we did before, we compared our codes and discussed and reconciled any discrepancies. We identified six relevant listener response categories: (a) Informational Support (offering informational support through providing advice, suggestions, feedback, or answering the sharer's questions); (b) Positive Socioemotional Support (emotionally supporting the sharer by empathizing with the sharer (e.g., "I understand you" or "I feel you"); approving of the sharer's decision/behavior, wishing the sharer luck, and/or expressing appreciation for the sharer's effort); (c) Negative Socioemotional Support (validating the sharer's feelings by blaming other parties such as a customer, manager, organization, or government as the causes of the sharer's reported problem); (d) Opposition (opposing the sharer's premise, scolding the sharer, or assigning blame to the sharer for the situation); (e) Reciprocal Sharing (sharing a personal experi-

TABLE 3 Examples of social coping behaviors and listener responses

Labeled construct	Post
Irrelevant Posts	
General Opinion/Other	… Since there are no sports on right now. Why don't they put essential workers on the front if the wheaties box for the time being. # essentialcover. (ID 102977)
Social Coping Behaviors	
Work Related-Informational Support Seeking	Is it okay for me to contact them and ask if they could reconsider me or not? Around March, I got a job offer from a company (A) that I applied for but I rejected it because I already changed my career path. … So I was already considering other companies and found one that I'm more interested in. But due to the pandemic the company (B) had a hiring freeze… I saw that company A is still hiring for the position I applied for. (ID 60461)
Work Related-Emotional Social Sharing (to vent)	I work in a state psych hospital … the hospital has cancelled all group activities until further notice, so the patients don't have the opportunity to get out and interact… My unit's had a huge spike in patient-on-patient altercations and patient-on-staff violence since the nursing homes stopped accepting new residents. I'm getting more burnt out and frustrated every shift the longer this goes on. **Just needed to get all this off my chest**. (ID 84698)
Work Related-Emotional Social Sharing (to seek support)	… things have been pretty scary… I'm truly terrified to return back to work. I got a phone call today from my boss that the company is now deemed essential work…I don't really know what to do and I've just been crying since the phone call. I thought I was strong but I'm anything but. I just wish I knew everything would be fine and that I didn't feel like I was needing to place my life on the line to be able to try and live. I'm so lost. … **I'm just really looking for some support**. (ID 256245)
Both Informational Support Seeking and Emotional Social Sharing	Tomorrow I'll have a zoom meeting with my boss where I'll tell him everything. First, I hate doing this over zoom, … Second, the timing is worse than ever. We are very understaffed … It's life and people quit all the time, but my boss has always been nice to me and I love working with him. I feel very bad and anxious at the moment. I know he'll get sad but I want to make sure this conversation goes as smoothly as possible I'd appreciate any advice you guys might have. Thanks. (ID 67487)
Listener Responses	
Informational Support	I would tell them you are looking to increase and round out your experience. As a student, you want to take the opportunity to explore work in different roles before you determine your career path. (ID 9924)
Positive Socioemotional Support	I'm glad you have reached out for help. … I know it must be extremely stressful. Getting overly stressed can wear you down. Hang in there! (ID 255702)
Negative Socioemotional Support	Only because our government is incapable of governing for the people instead of the corporations. (ID 262657)
Opposition	How about you stop blaming the populace and start blaming the people in charge you flaming asshole? (ID 6438)
Reciprocal Sharing	… As a married full time working from home with my children mom I feel impatient and frustrated with my kids. You are not alone. (ID 106740)
Reframing	Don't beat yourself up too hard. Mistakes happen. It sounds like you did the best you could in that situation. Every mistake has multiple root causes. Here you were overwhelmed with brand new admits at shift change which should not have happened and your coworkers weren't being helpful. … At the end of the day, don't dwell on the mistakes, but think about them and what you, your manager, your team can do differently. (ID 437904)

TABLE 4 Mean algorithm performance metrics

	Classifying Work-Related Posts and Social Coping Behaviors						Classifying Listener Responses											
	Work-Related		Emotional Social Sharing		Informational Support Seeking		Informational Support		Positive Socioemotional Support		Negative Socioemotional Support		Opposition		Reciprocal Sharing		Reframing	
	A	F1	A	F1	A	F1	A	F1	A	F1	A	F1	A	F1	A	F1	A	F1
Naïve Bayes	87%	89%	91%	92%	94%	95%	80%	77%	79%	81%	82%	80%	79%	77%	93%	92%	65%	65%
Support Vector Machine	**95%**	**95%**	**94%**	**94%**	**95%**	**96%**	81%	78%	90%	90%	86%	86%	95%	95%	88%	87%	78%	75%
Logistic Regression	83%	83%	87%	87%	82%	83%	**83%**	**81%**	**90%**	**90%**	86%	85%	90%	90%	**95%**	**95%**	71%	71%
Random Forest	89%	89%	88%	89%	90%	91%	81%	79%	81%	82%	**88%**	**88%**	**93%**	**93%**	93%	92%	**83%**	**82%**
Train Size	391		274		204		336		295		233		296		280		178	
Test Size	167		117		87		144		126		100		126		120		77	
Validation Size	150		150		150		150		150		150		150		150		150	
Best algorithm & Validation sample	98%		93%		90%		82%		86%		88%		89%		88%		80%	

(Continues)

TABLE 4 (Continued)

	Classifying Occupational Contexts													
	Educators		Food Service Workers		Healthcare Workers		Office/ Corporate Workers		Other Services Workers		Retail Workers		Unemployed	
	A	F1	A	F1	A	F1	A	F1	A	F1	A	F1	A	F1
Naïve Bayes	80%	78%	90%	89%	90%	90%	91%	90%	83%	80%	87%	86%	82%	82%
Support Vector Machine	81%	81%	88%	88%	95%	95%	94%	94%	83%	83%	92%	92%	85%	85%
Logistic Regression	82%	82%	92%	92%	94%	93%	**95%**	**95%**	**83%**	**83%**	**92%**	**92%**	**85%**	**85%**
Random Forest	**82%**	**81%**	**95%**	**94%**	**96%**	**95%**	92%	91%	80%	79%	90%	90%	84%	84%
Train Size	517		329		5605		3980		325		2825		438	
Test Size	221		141		2402		1706		139		1211		188	
Validation Size	150		150		150		150		150		150		150	
Best algorithm &Validation sample	81%		91%		94%		95%		81%		94%		81%	

Note. A = Accuracy; F1 = F1-score, Last row shows the agreement between the best algorithm and RAs in classifying the validation sample.

TABLE 5 Agreements between machine learning model, LIWC, and manual labeling

Methods	Anger/Disgust	Sadness	Fear
Manual Labeling by RAs			
All RAs agreed upon	237 posts	220 posts	254 posts
Inter-Rater Reliability (α)	.86	.82	.90
LIWC	181/237 (76.4%)	174/220 (79.1%)	189/254 (74.4%)
Machine Learning	204/237 (86.1%)	203/220 (92.3%)	221/254 (87.0%)

Note. Three RAs labeled 300 reaction posts independently.

ence); and (f) Reframing (reframing the stressor and encouraging the sharer to look at the stressor from different angles). Some listeners used a combination of these responses and a small number did not use any of them, typically because they included clarifying questions, general comments, or opinions about the post. We grouped these remaining responses together and labeled this category *Other*. Table 2 displays examples of each response category from our data.

Next, we selected a random sample of 1,000 responses and asked two RAs to independently categorize them into the six dummy variables representing each category. Each post may belong to more than one category. We compared the performance of (a) supervised ML, (b) word-embedding, and (c) supervised ML augmented with word-embedding in terms of each method's ability to categorize the data into the response categories (for technical details, please see Appendix A). The augmented model outperformed the other models. We used the highest performing algorithm (see Table 4) to categorize the data in each response category.

2.11 | Sharer-listener occupational category match

Next, we sought to identify whether each sharer-listener pair were part of the same occupational category or not. To classify Redditors into occupations, we first created a ground truth sample by asking the RAs to read a random sample of 200 posts and responses and to record any mentions of the sharers' or listeners' occupations. Next, we reviewed this list of occupations and grouped them by similarity into seven categories: (a) healthcare workers, (b) retail workers, (c) educators, (d) food services workers (e) office/corporate workers, (f) other service workers, and (g) unemployed people.

To increase the size of the labeled sample we used the regular expression method (Aho, 1991) and searched the entire post history of each Redditor (Dataset 3) to find any patterns that revealed the person's occupational category (e.g., "I work at," "I [was|am|have been] [laid off|furloughed]," "I [have been|] [work|working],"). Using this method we identified the occupational category of 9,968 more Redditors, which, along with those that were hand coded, resulted in occupational categorizations of 10,168 Redditors. Using Dataset 2, we also know the subreddits in which all of the Redditors in our sample are active, including these newly labeled Redditors. From this we created a ground truth dataset of 10,168 Redditors whose subreddit activities are the features (inputs) and occupational categories are the labels (output).

Next, we used random under-sampling to create a balanced dataset of each of the labeled categories to train and test the algorithms. We used the best algorithm to classify the remaining Redditors into the occupational categories (see Table 4 for the performance of each algorithm). With each Redditor classified into an occupational category, we were able to simply code each sharer-listener pair as 1 (same occupational category) or 0 (different occupational categories).

2.12 | Sharer's affective reactions to the responses

Finally, we wanted to measure the sharer's affective reactions to the conversation (hereafter, reactions) in terms of their level of satisfaction and the amount of anger, sadness, and fear reflected in their subsequent posts. To do this, we examined comments by sharers who returned to the conversation and responded with further comments or updates. Sharers returned in 6,093 out of 9,371 conversations.[2] We then used the Word2Vec method to measure the degree of satisfaction and discrete emotions (anger, sadness, and fear) reflected in the reactions. For satisfaction, we used the average of the 300-dimensional vectors for "happy" and "satisfied." For each of the discrete emotions, we used the same method that was used previously when labeling the discrete emotions in the original post. These reactions were all averaged at the level of the conversation, representing the average level of the sharer's affective reaction to the conversation. To validate the Word2Vec approach, our RAs categorized a random sample of 300 reaction posts based on whether they seemed to reflect satisfaction with the conversation and whether the reactions seemed to reflect anger, sadness, or fear (all coded 1 for yes and 0 for no). The inter-rater reliability was high ($\alpha_{\text{satisfaction}} = 83\%$, $\alpha_{\text{anger}} = 86\%$, $\alpha_{\text{sadness}} = 82\%$, $\alpha_{\text{fear}} = 90\%$). In addition, the agreement between the manually labeled reactions (where there was consensus between the three RAs) and the algorithmically labeled reactions were strong: 82% for satisfaction, 86.1% for anger, 92.3% for sadness, and 87% for fear.

It should be noted that using algorithms to measure individuals' felt emotions through online posts has been previously debated. For example, Kross et al. (2019) evaluated whether the emotion words used in Facebook posts can accurately represent felt emotions. They did so by comparing the performance of Linguistic Inquiry and Word Count (LIWC), a text analysis program that counts emotion words (Pennebaker et al., 2007), with the performance of human judges in terms of predicting the self-reported felt emotions of the sharers. They found that, unlike LIWC, the human judges' ratings of the emotionality of posts consistently predicted how people felt. This finding supports the notion that human categorization of emotions reflected in social media text can be used as a ground truth to validate algorithmic classification of emotions.

To test this in our own data, we also used LIWC to measure anger, anxiety, and sadness in the reactions and compared the performance of this method with our Word Embedding approach, using the ground truth sample. Table 5 shows that Word Embedding consistently outperformed LIWC in categorizing emotions similarly to human judges. Therefore, we believe the use of Word Embedding, and more specifically, the Word2Vec method is an appropriate way to label reflected emotions in the reaction posts. It should be noted, however, that these are still proxies for felt emotion and may be conservatively interpreted as communicated emotion.

Figure 3 shows the final conceptual model, which includes the specific types of stressors, social coping behaviors, occupational contexts, and listener responses that emerged from the data as well as the sharer reactions we labeled. The arrows in the model represent the relationships between components that we will explore in the results section.

3 | RESULTS

Descriptive statistics of all the variables we extracted from the textual data are presented in Table 6 and correlation tables for these variables are available in Tables S2 and S3 in the online supplementary document. First, we noted some interesting relationships between different listener responses. For example, the data show that informational support, reciprocal sharing, and reframing are all moderately to highly correlated with each other, with correlations of .29 (informational support and reciprocal sharing), .46 (informational support and reframing), and .50 (reciprocal sharing and reframing). What seems to be common among these is that they represent "cooler," more cognitive approaches to responding. Informational support often included advice about what to do, reciprocal sharing

TABLE 6 Descriptive statistics of study variables

Variable	*n*	*M*	*SD*
Work-Related Stressors			
Career Path Ambiguity	9,371	.05	0.12
Job Search/Application Ambiguity	9,371	.08	0.12
Concerns about Viability of Quitting	9,371	.08	0.10
Resignation/Onboarding Process Ambiguity	9,371	.04	0.08
HR/Management-Related Issues	9,371	.05	0.11
Unemployment Assistance Issues	9,371	.07	0.15
Inadequacy of Compensation and Benefits	9,371	.04	0.08
Scheduling Mismanagement	9,371	.06	0.10
Work-Family Conflict	9,371	.04	0.10
Disrespectful Workplace Environments	9,371	.04	0.07
Mismanagement of EDI Issues	9,371	.03	0.08
Workplace Exploitation	9,371	.02	0.07
Interpersonal Conflict	9,371	.04	0.09
Essential Work Concerns	9,371	.04	0.10
Field-Specific Teaching Concerns	9,371	.01	0.05
Field-Specific Nursing Concerns	9,371	.05	0.12
Field-Specific Postal Work Concerns	9,371	.02	0.08
Retail Worker Concerns	9,371	.03	0.09
Social Coping Behaviors			
Informational Support Seeking	9,371	.61	0.09
Sharing Anger[a]	9,371	.36	0.12
Sharing Sadness	9,371	.41	0.11
Sharing Fear	9,371	.44	0.12
Listener Responses			
Informational Support	136,458	.47	0.16
Positive Socioemotional Support	136,429	.4	0.14
Negative Socioemotional Support	136,458	.52	0.38
Opposition	136,458	.27	0.07
Reciprocal Sharing	136,458	.43	0.43
Reframing	136,429	.14	0.09
Sharer Affective Reactions			
Satisfaction	6,093	.48	0.51
Anger[a]	6,093	.02	0.43
Sadness	6,093	.14	0.32
Fear	6,093	.53	0.44

Note. Discrete emotions are normalized between 0 and 1. The rest of the variables are probability values.
[a]Measures of anger represents both anger and disgust combined.

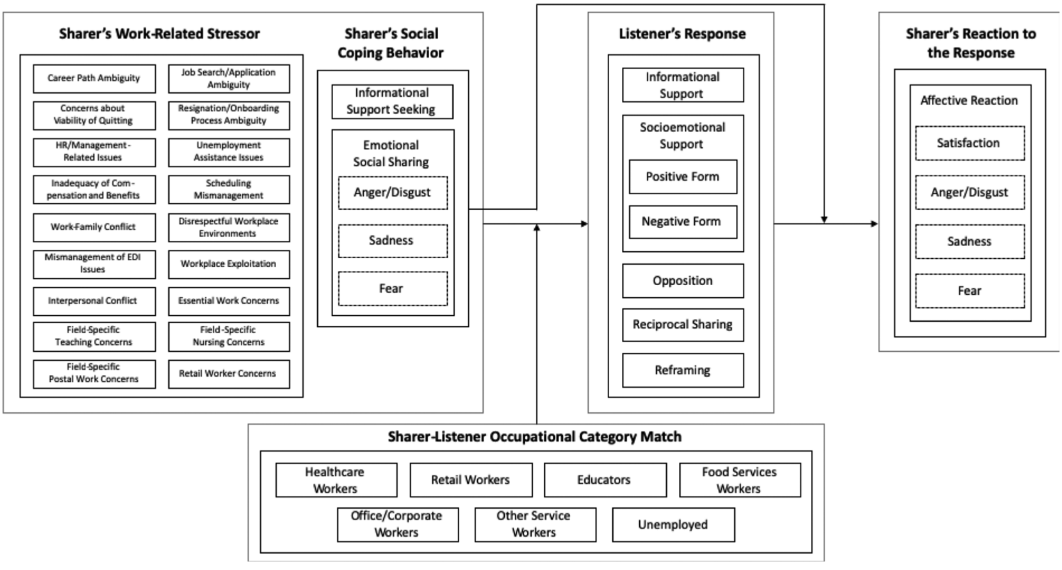

FIGURE 3 Theoretical model based on findings

appeared to be used often as a way to demonstrate how to address a problem through the lens of the listener's own personal experience, and reframing involved appeals to appraise the situation differently. The other pattern we identified is that informational support was negatively related to positive socioemotional support ($r = -.16$) and negative socioemotional support ($r = -.14$). One interpretation of this pattern is that socioemotional support is used as a response when listeners do not have useful information or advice to offer. Finally, we note that negative socioemotional support and opposition are positively related ($r = .11$), perhaps suggesting a general negative emotional tone in the conversation and/or the discussion of controversial or polarizing issues.

Next, we addressed our research questions, which were motivated by a desire to better understand the dynamic process of online social coping. To do so, we examined the cues that listeners use to respond to online social coping attempts and the impact of both those cues and listeners' responses on the affective reactions of the sharer. Given that our quantitative models comprise many variables, we only report significant findings that indicate a theoretically-meaningful pattern in the text, and direct the reader to Tables 7–8 for the details of these results.

3.1 | Research Question 1 and 2

Our first two research questions refer to the cues (work-related stressors and social coping behaviors) that influence the listener's response and the moderating role of the occupational context match. As presented in Table 7, considering that posts are nested within conversations, we examined these relationships using multi-level regression models of each of the responses (informational support, positive socioemotional support, negative socioemotional support, opposition, reciprocal sharing, and reframing) on coping behaviors (seeking informational support, sharing anger, sharing fear, and sharing sadness), the 18 work-related stressors, occupational context match, and the interactions between these two sets of cues and occupational context match. There are several significant relationships for both stressors and coping behaviors, indicating that, overall, listeners respond to these two cues independently.

TABLE 7 Regression results of listener's responses on work-related stressors, social coping behaviors, and occupational context match

	Informational Support		Positive Socioemotional Support		Negative Socioemotional Support		Opposition		Reciprocal Sharing		Reframing	
	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8	Model9	Model10	Model11	Model12
Occupational Context Match	.04***	.01	.02***	–.03**	.02***	–.00	–.02***	.03***	.16***	–.01	.02***	–.04***
	(.00)	(.01)	(.00)	(.01)	(.00)	(.03)	(.00)	(.01)	(.00)	(.04)	(.00)	(.01)
Career Path Ambiguity	.13***	.14***	–.07***	–.08***	–.31***	–.31***	–.01**	–.01	–.08**	–.06+	.05***	.03***
	(.01)	(.01)	(.01)	(.01)	(.02)	(.03)	(.00)	(.01)	(.03)	(.04)	(.01)	(.01)
Job Search/Application Ambiguity	.08***	.08***	–.08***	–.06***	–.24***	–.22***	–.01	–.01*	–.19***	–.13***	.01	.01
	(.01)	(.01)	(.01)	(.01)	(.02)	(.03)	(.00)	(.01)	(.03)	(.04)	(.01)	(.01)
Concerns about Viability of Quitting	.07***	.08***	–.04***	–.03*	–.22***	–.21***	–.06***	–.05***	.14***	.17***	.08***	.06***
	(.01)	(.01)	(.01)	(.01)	(.03)	(.03)	(.01)	(.01)	(.03)	(.04)	(.01)	(.01)
Resignation/Onboarding Process Ambiguity	.02	.01	–.00	–.02	.05+	–.01	–.02***	–.01	.12***	.04	.01	–.01
	(.01)	(.02)	(.01)	(.01)	(.03)	(.04)	(.01)	(.01)	(.03)	(.04)	(.01)	(.01)
HR/Management-Related Issues	.17***	.16***	–.02+	–.02+	–.06*	–.08*	–.04***	–.04***	.09**	.08*	.13***	.10***
	(.01)	(.01)	(.01)	(.01)	(.02)	(.03)	(.00)	(.01)	(.03)	(.04)	(.01)	(.01)
Unemployment Assistance Issues	–.01	–.03**	–.03***	–.01	.04+	.04	.01**	.01*	–.13***	–.12***	–.02***	–.03***
	(.01)	(.01)	(.01)	(.01)	(.02)	(.03)	(.00)	(.01)	(.02)	(.03)	(.01)	(.01)
Inadequacy of Compensation and Benefits	.06***	.01	–.16***	–.12***	–.07**	–.13***	–.02***	–.00	–.12***	–.21***	.02***	.00
	(.01)	(.01)	(.01)	(.01)	(.03)	(.03)	(.01)	(.01)	(.03)	(.04)	(.01)	(.01)
Scheduling Mismanagement	–.08***	–.07***	.02*	.02	.17***	.14***	–.01**	–.01	.12***	.11**	–.01	–.01
	(.01)	(.01)	(.01)	(.01)	(.02)	(.03)	(.00)	(.01)	(.03)	(.04)	(.01)	(.01)
Work-Family Conflict	.04***	.06***	.07***	.08***	–.39***	–.37***	–.08***	–.09***	.45***	.63***	.04***	.06***
	(.01)	(.01)	(.01)	(.01)	(.02)	(.03)	(.00)	(.01)	(.03)	(.03)	(.01)	(.01)
Disrespectful Workplace Environments	.01	.02	.04**	.04*	.13***	.08*	–.02***	–.02**	.10**	.13**	.11***	.09***
	(.01)	(.02)	(.01)	(.02)	(.03)	(.04)	(.01)	(.01)	(.04)	(.05)	(.01)	(.01)

(Continues)

TABLE 7 (Continued)

	Informational Support		Positive Socioemotional Support		Negative Socioemotional Support		Opposition		Reciprocal Sharing		Reframing	
	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8	Model9	Model10	Model11	Model12
Mismanagement of EDI Issues	.09***	.10***	–.09***	–.10***	.23***	.17***	–.01	–.01	–.10**	–.13***	.03***	.02*
	(.01)	(.01)	(.01)	(.01)	(.03)	(.03)	(.01)	(.01)	(.03)	(.04)	(.01)	(.01)
Workplace Exploitation	–.05***	–.12***	–.08***	–.05**	.04	.06	–.00	.00	–.14***	–.08+	–.00	–.01
	(.01)	(.02)	(.01)	(.02)	(.03)	(.04)	(.01)	(.01)	(.04)	(.04)	(.01)	(.01)
Interpersonal Conflict	.02	.01	.00	–.00	.25***	.22***	–.01+	–.01	.07*	.08+	.06***	.05***
	(.01)	(.01)	(.01)	(.01)	(.03)	(.03)	(.01)	(.01)	(.03)	(.04)	(.01)	(.01)
Essential Work Concerns	–.07***	–.08***	–.04***	–.04**	.19***	.17***	.02***	.03***	–.07*	–.13***	–.02*	–.03***
	(.01)	(.01)	(.01)	(.01)	(.02)	(.03)	(.01)	(.01)	(.03)	(.04)	(.01)	(.01)
Field-Specific Teaching Concerns	.08***	.04+	.06***	.06**	–.32***	–.27***	–.03***	–.01	.11*	.02	.00	–.02
	(.02)	(.02)	(.01)	(.02)	(.04)	(.05)	(.01)	(.01)	(.04)	(.06)	(.01)	(.01)
Field-Specific Nursing Concerns	–.03***	–.19***	.12***	.12***	.20***	.04	–.01***	.01*	.18***	–.42***	.00	–.05***
	(.01)	(.01)	(.01)	(.01)	(.02)	(.03)	(.00)	(.01)	(.03)	(.04)	(.01)	(.01)
Field-Specific Postal Work Concerns	–.06***	–.07***	.01	.00	.11***	.07*	.01*	.01+	.04	–.01	–.01+	–.02*
	(.01)	(.01)	(.01)	(.01)	(.03)	(.03)	(.01)	(.01)	(.03)	(.04)	(.01)	(.01)
Retail Worker Concerns	–.11***	–.14***	.00	.02	.17***	.22***	.05***	.04***	–.00	.13***	–.02***	–.03***
	(.01)	(.01)	(.01)	(.01)	(.02)	(.03)	(.01)	(.01)	(.03)	(.04)	(.01)	(.01)
Informational Support Seeking	.18***	.18***	–.04**	–.08***	–.12***	–.07+	–.12***	–.08***	.29***	.26***	.10***	.08***
	(.01)	(.02)	(.01)	(.02)	(.03)	(.04)	(.01)	(.01)	(.03)	(.05)	(.01)	(.01)
Sharing Anger[a]	–.19***	–.18***	–.06***	–.03**	.12***	.13***	.06***	.04***	–.16***	–.17***	–.10***	–.09***
	(.01)	(.01)	(.01)	(.01)	(.02)	(.02)	(.00)	(.00)	(.02)	(.03)	(.01)	(.01)
Sharing Sadness	.05***	.03***	.02**	.02*	–.06***	–.05*	–.01**	–.01*	.02	.01	.02***	.02***
	(.01)	(.01)	(.01)	(.01)	(.02)	(.02)	(.00)	(.00)	(.02)	(.02)	(.00)	(.01)
Sharing Fear	.05***	.04***	.08***	.03*	.11***	.05+	–.03***	–.01**	.20***	.08*	.15***	.10***
	(.01)	(.01)	(.01)	(.01)	(.02)	(.03)	(.00)	(.01)	(.02)	(.03)	(.01)	(.01)

(Continues)

TABLE 7 (Continued)

	Informational Support		Positive Socioemotional Support		Negative Socioemotional Support		Opposition		Reciprocal Sharing		Reframing	
	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8	Model9	Model10	Model11	Model12
Occupational Context Match × Career Path Ambiguity		–.01		.02		.00		–.01		–.03		.03**
		(.01)		(.01)		(.03)		(.01)		(.04)		(.01)
Occupational Context Match × Job Search/Application Ambiguity		–.00		–.03*		–.04		.01+		–.08*		–.01
		(.01)		(.01)		(.03)		(.01)		(.04)		(.01)
Occupational Context Match × Concerns about Viability of Quitting		–.02+		–.01		–.01		–.01+		–.06		.02**
		(.01)		(.01)		(.03)		(.01)		(.04)		(.01)
Occupational Context Match × Resignation/Onboarding Process Ambiguity		.01		.03*		.09*		–.02**		.12**		.04***
		(.02)		(.02)		(.04)		(.01)		(.05)		(.01)
Occupational Context Match × HR/Management-Related Issues		.02		.01		.02		–.01*		.01		.04***
		(.01)		(.01)		(.03)		(.01)		(.04)		(.01)
Occupational Context Match × Unemployment Assistance Issues		.03**		–.02*		.00		–.00		–.01		.02*
		(.01)		(.01)		(.03)		(.01)		(.03)		(.01)
Occupational Context Match × Inadequacy of Compensation and Benefits		.09***		–.06***		.09**		–.03***		.14***		.03***
		(.01)		(.01)		(.03)		(.01)		(.04)		(.01)
Occupational Context Match × Scheduling Mismanagement		–.02+		.01		.05		–.01+		.02		.01
		(.01)		(.01)		(.03)		(.01)		(.04)		(.01)
Occupational Context Match × Work-Family Conflict		–.05***		–.02+		–.04		.02**		–.33***		–.04***
		(.01)		(.01)		(.03)		(.01)		(.03)		(.01)
Occupational Context Match × Disrespectful Workplace Environments		–.02		–.00		.08*		.00		–.07		.03**
		(.02)		(.01)		(.04)		(.01)		(.04)		(.01)
Occupational Context Match × Mismanagement of EDI Issues		–.02		.03*		.09*		–.00		.05		.01
		(.01)		(.01)		(.04)		(.01)		(.04)		(.01)
Occupational Context Match × Workplace Exploitation		.12***		–.06***		–.04		–.01		–.11**		.02+
		(.02)		(.01)		(.04)		(.01)		(.04)		(.01)

(Continues)

TABLE 7 (Continued)

	Informational Support		Positive Socioemotional Support		Negative Socioemotional Support		Opposition		Reciprocal Sharing		Reframing	
	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8	Model9	Model10	Model11	Model12
Occupational Context Match × Interpersonal Conflict		.00		.01		.05		–.00		.00		.01
		(.01)		(.01)		(.03)		(.01)		(.04)		(.01)
Occupational Context Match × Essential Work Concerns		.03*		–.01		.03		–.01		.11**		.02**
		(.01)		(.01)		(.03)		(.01)		(.04)		(.01)
Occupational Context Match × Field-Specific Teaching Concerns		.05*		–.00		–.06		–.02*		.12*		.03*
		(.02)		(.02)		(.05)		(.01)		(.06)		(.01)
Occupational Context Match × Field-Specific Nursing Concerns		.20***		–.00		.21***		–.04***		.73***		.07***
		(.01)		(.01)		(.03)		(.01)		(.03)		(.01)
Occupational Context Match × Field-Specific Postal Work Concerns		.02		.01		.08*		.00		.09*		.01
		(.01)		(.01)		(.03)		(.01)		(.04)		(.01)
Occupational Context Match × Retail Worker Concerns		.05***		–.03*		–.07*		.01*		–.20***		.01
		(.01)		(.01)		(.03)		(.01)		(.04)		(.01)
Occupational Context Match × Informational Support Seeking		–.01		.07***		–.07+		–.07***		.07		.04***
		(.02)		(.01)		(.04)		(.01)		(.04)		(.01)
Occupational Context Match × Sharing Anger[a]		–.01		–.05***		–.01		.02***		.01		–.02***
		(.01)		(.01)		(.02)		(.00)		(.03)		(.01)
Occupational Context Match × Sharing Sadness		.03**		–.00		–.02		–.00		.00		.00
		(.01)		(.01)		(.02)		(.00)		(.02)		(.01)
Occupational Context Match × Sharing Fear		.01		.09***		.10***		–.03***		.21***		.08***
		(.01)		(.01)		(.03)		(.00)		(.03)		(.01)
Intercept	.37***	.39***	.39***	.43***	.49***	.50***	.36***	.33***	.12***	.22***	.02**	.06***
	(.01)	(.01)	(.01)	(.01)	(.03)	(.03)	(.01)	(.01)	(.03)	(.04)	(.01)	(.01)
R^2	.14	.15	.08	.08	.11	.11	.11	.11	.06	.08	.11	.11

Note. $N = 136{,}458$ for Model 1, 2, 5–10. $N = 136{,}429$ for Model 3, 4, 11, and 12. Adjusted Standard Error for clusters (of conversation) in parenthesis. Occupational Context Match is coded as 1 = Match, 0 = No Match. The 18-topic STM model generated 18 probability variables based on the probability distribution of the posts over these 18 topics. Therefore, the 18 topics initially added to 1. To avoid perfect collinearity, when entering these topics in the regression model, we rounded them to one decimal point such that a random residual with the expected value of zero was generated and the topics no longer added to one.

[a]Measure of anger represents both anger and disgust combined.

$^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

TABLE 8 Regression results of sharer's affective reactions on work-related stres listener responses

	Satisfaction		Anger/Disgust		Sadness		Fear	
	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8
Informational Support	.09***	.13	−.16***	−.24*	.02**	−.09	−.04***	−.51***
	(.01)	(.13)	(.01)	(.11)	(.01)	(.08)	(.01)	(.11)
Positive Socioemotional Support	.05***	−.64***	−.01	.47***	.02*	.24**	.01	.48***
	(.01)	(.14)	(.01)	(.11)	(.01)	(.08)	(.01)	(.11)
Negative Socioemotional Support	−.16***	−.41**	.08***	.41***	.05***	−.17*	.07***	.49***
	(.01)	(.15)	(.01)	(.12)	(.01)	(.09)	(.01)	(.12)
Opposition	−.18***	−.43	.04+	−.44	.05**	−.51**	.00	−.73**
	(.03)	(.33)	(.02)	(.27)	(.02)	(.19)	(.02)	(.27)
Reciprocal Sharing	.01	−.05	.03***	−.02	−.01+	−.09+	.02**	−.32***
	(.01)	(.09)	(.01)	(.07)	(.00)	(.05)	(.01)	(.07)
Reframing	.10***	−.90***	−.07***	.26	.13***	−.10	.13***	.20
	(.02)	(.24)	(.02)	(.19)	(.01)	(.14)	(.02)	(.19)
Informational Support Seeking	.55***	−.10	−.75***	−.41*	.18***	−.13	−.48***	−.71***
	(.03)	(.20)	(.02)	(.16)	(.02)	(.12)	(.02)	(.16)
Sharing Anger[a]	−.70***	−.54***	.90***	.77***	−.17***	−.27***	.02	.13
	(.02)	(.14)	(.01)	(.11)	(.01)	(.08)	(.01)	(.11)
Sharing Sadness	−.12***	.29*	−.04***	−.45***	.56***	.47***	.04**	−.08
	(.01)	(.12)	(.01)	(.10)	(.01)	(.07)	(.01)	(.10)
Sharing Fear	.44***	−.47**	−.34***	.09	.24***	.16+	.74***	.63***
	(.02)	(.15)	(.02)	(.12)	(.01)	(.09)	(.02)	(.12)
Career Path Ambiguity	.44***	.44***	−.10***	−.09***	.13***	.12***	.00	.01
	(.02)	(.02)	(.02)	(.02)	(.01)	(.01)	(.02)	(.02)
Job Search/Application Ambiguity	.56***	.55***	−.27***	−.25***	−.01	−.01	.08***	.09***
	(.02)	(.02)	(.02)	(.02)	(.01)	(.01)	(.02)	(.02)

(Continues)

TABLE 8 (Continued)

	Satisfaction		Anger/Disgust		Sadness		Fear	
	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8
Concerns about Viability of Quitting	.62***	.62***	–.13***	–.13***	.05***	.05***	.19***	.18***
	(.02)	(.02)	(.02)	(.02)	(.01)	(.01)	(.02)	(.02)
Resignation/Onboarding Process Ambiguity	.16***	.15***	–.03	–.02	.08***	.08***	.02	.03
	(.03)	(.03)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)
HR/Management–Related Issues	.44***	.44***	–.34***	–.33***	.11***	.11***	–.15***	–.14***
	(.02)	(.02)	(.02)	(.02)	(.01)	(.01)	(.02)	(.02)
Unemployment Assistance Issues	.36***	.36***	–.27***	–.26***	.03*	.03**	.07***	.08***
	(.02)	(.02)	(.02)	(.02)	(.01)	(.01)	(.02)	(.02)
Inadequacy of Compensation and Benefits	–.25***	–.26***	–.10***	–.10***	.15***	.15***	.11***	.11***
	(.03)	(.03)	(.02)	(.02)	(.01)	(.01)	(.02)	(.02)
Scheduling Mismanagement	.15***	.15***	.19***	.19***	.12***	.12***	.27***	.27***
	(.02)	(.02)	(.02)	(.02)	(.01)	(.01)	(.02)	(.02)
Work-Family Conflict	.65***	.65***	–.28***	–.27***	.02	.02	.21***	.20***
	(.02)	(.02)	(.02)	(.02)	(.01)	(.01)	(.02)	(.02)
Disrespectful Workplace Environments	.51***	.50***	–.21***	–.21***	.11***	.10***	.06**	.06**
	(.03)	(.03)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)
Mismanagement of EDI Issues	–.18***	–.18***	–.11***	–.11***	.29***	.29***	.17***	.17***
	(.03)	(.03)	(.02)	(.02)	(.01)	(.01)	(.02)	(.02)
Workplace Exploitation	.15***	.14***	–.20***	–.19***	.09***	.09***	–.15***	–.16***
	(.03)	(.03)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)
Interpersonal Conflict	.06*	.06*	–.05**	–.05*	.08***	.08***	.15***	.16***
	(.02)	(.02)	(.02)	(.02)	(.01)	(.01)	(.02)	(.02)
Essential Work Concerns	.42***	.42***	–.46***	–.45***	.06***	.06***	–.14***	–.14***
	(.02)	(.02)	(.02)	(.02)	(.01)	(.01)	(.02)	(.02)

(Continues)

TABLE 8 (Continued)

	Satisfaction		Anger/Disgust		Sadness		Fear	
	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8
Field-Specific Teaching Concerns	.33***	.32***	−.47***	−.47***	−.25***	−.25***	−.14***	−.15***
	(.03)	(.03)	(.03)	(.03)	(.02)	(.02)	(.03)	(.03)
Field-Specific Nursing Concerns	.30***	.30***	−.04*	−.04*	.01	.01	.20***	.20***
	(.02)	(.02)	(.02)	(.02)	(.01)	(.01)	(.02)	(.02)
Field-Specific Postal Work Concerns	.22***	.22***	.08***	.08***	−.03*	−.04**	.13***	.13***
	(.02)	(.02)	(.02)	(.02)	(.01)	(.01)	(.02)	(.02)
Retail Worker Concerns	.23***	.23***	.16***	.16***	−.13***	−.13***	.26***	.25***
	(.02)	(.02)	(.02)	(.02)	(.01)	(.01)	(.02)	(.02)
Score of Up/Downvote	−.78***	−.78***	.43***	.43***	.05	.04	−.49***	−.48***
	(.11)	(.11)	(.09)	(.09)	(.06)	(.06)	(.09)	(.09)
Informational Support × Informational Support Seeking		.06		−.03		.16		.36**
		(.16)		(.13)		(.10)		(.13)
Informational Support × Sharing Anger[a]		−.35**		.05		.08		−.29**
		(.12)		(.09)		(.07)		(.10)
Informational Support × Sharing Sadness		−.15		−.07		.02		−.02
		(.10)		(.08)		(.06)		(.08)
Informational Support × Sharing Fear		.26*		.24*		−.04		.81***
		(.12)		(.10)		(.07)		(.10)
Positive Socioemotional Support × Informational Support Seeking		.65***		−.50***		−.16		−.48***
		(.17)		(.14)		(.10)		(.14)
Positive Socioemotional Support × Sharing Anger[a]		−.06		.02		−.21**		−.28**
		(.12)		(.10)		(.07)		(.10)
Positive Socioemotional Support × Sharing Sadness		.06		.17*		−.03		.06
		(.11)		(.09)		(.06)		(.09)

(Continues)

TABLE 8 (Continued)

	Satisfaction		Anger/Disgust		Sadness		Fear	
	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8
Positive Socioemotional Support × Sharing Fear		.64***		−.55***		−.07		−.21*
		(.13)		(.10)		(.07)		(.10)
Negative Socioemotional Support × Informational Support Seeking		.16		−.32*		.15		−.21
		(.18)		(.15)		(.11)		(.15)
Negative Socioemotional Support × Sharing Anger[a]		.22+		−.17		.01		−.16
		(.13)		(.10)		(.08)		(.11)
Negative Socioemotional Support × Sharing Sadness		−.14		.10		.21**		−.16+
		(.12)		(.09)		(.07)		(.09)
Negative Socioemotional Support × Sharing Fear		.25+		−.24*		.10		−.32**
		(.14)		(.11)		(.08)		(.11)
Opposition × Informational Support Seeking		.40		.00		.72**		.58+
		(.40)		(.33)		(.24)		(.33)
Opposition × Sharing Anger[a]		−.06		.54*		.45**		.77**
		(.29)		(.24)		(.17)		(.24)
Opposition × Sharing Sadness		−.52*		.88***		−.42**		.43*
		(.26)		(.21)		(.15)		(.21)
Opposition × Sharing Fear		.52+		−.20		.28		−.16
		(.30)		(.25)		(.18)		(.25)
Reciprocal Sharing × Informational Support Seeking		.08		.15+		−.08		.36***
		(.11)		(.09)		(.06)		(.09)
Reciprocal Sharing × Sharing Anger[a]		−.14+		.10+		.01		.01
		(.08)		(.06)		(.05)		(.06)
Reciprocal Sharing × Sharing Sadness		−.11+		−.01		.25***		.09+
		(.07)		(.05)		(.04)		(.05)

(Continues)

TABLE 8 (Continued)

	Satisfaction		Anger/Disgust		Sadness		Fear	
	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8
Reciprocal Sharing × Sharing Fear		.23**		−.16*		.06		.19**
		(.08)		(.06)		(.05)		(.06)
Reframing × Informational Support Seeking		1.11***		−.37		.49**		.25
		(.29)		(.24)		(.17)		(.24)
Reframing × Sharing Anger[a]		−.04		−.10		.04		−.10
		(.21)		(.17)		(.12)		(.17)
Reframing × Sharing Sadness		−.84***		.67***		.06		.11
		(.18)		(.15)		(.11)		(.15)
Reframing × Sharing Fear		1.41***		−.69***		−.18		−.47**
		(.21)		(.17)		(.13)		(.17)
Intercept	.03	.63***	.46***	.26*	−.36***	−.08	.39***	.57***
	(.03)	(.16)	(.02)	(.13)	(.02)	(.09)	(.02)	(.13)
R^2	.14	.14	.22	.22	.13	.13	.15	.15

Note. $N = 77{,}708$. Adjusted Standard Error for clusters (of conversation) in parenthesis.

[a]Measure of anger represents both anger and disgust combined.

$^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

3.2 | Relationship between work-related stressors and listener responses

A key dimension by which the stressors seem to vary is how occupation-specific or universal they are. For example, we found several stressors that are explicitly field-specific (e.g., nursing, postal work, retail), but also many that represent concerns that employees may face in any occupation (e.g., HR/Management-related issues, work-family conflict). A salient pattern of relationships between work-related stressors and listener responses is that the more universal stressors are more likely to invite informational support. For example, Table 7 shows that the probability of providing informational support was positively related to career path ambiguity ($b = .14$, $p < .001$), HR/management-related issues ($b = .16$, $p < .001$), mismanagement of EDI issues ($b = .10$, $p < .001$), work-family conflict ($b = .06$, $p < .001$), concerns about viability of quitting ($b = .08$, $p < .001$), and job search/application ambiguity ($b = .08$, $p < .001$). This could be because these are all issues that many employees face and listeners are less likely to need specific occupational knowledge to respond.

Conversely, we found that stressors that are tied to specific occupations were met with less informational support. This included essential work concerns ($b = -.08$, $p < .001$), field-specific nursing concerns ($b = -.19$, $p < .001$), field-specific postal work concerns ($b = -.07$, $p < .001$), and retail worker concerns ($b = -.14$, $p < .001$). However, the occupational context match mitigated these negative relationships, such that listeners with similar occupational contexts as the sharers were more likely to provide informational support for occupation-specific stressors. This interaction was observed for essential work concerns ($b = .03$, $p < .05$), nursing concerns ($b = .20$, $p < .001$), and retail worker concerns ($b = .05$, $p < .001$). Figure B1 in Appendix B shows the plot of these interactions. Together, this pattern of findings suggests:

> *P1. Listeners* are *less (vs. more) likely to respond to types of stressors that are (are not) occupationally specific with informational support.*

> *P2. The negative relationship* between *occupational specificity of the shared stressor and informational support is mitigated by occupational context match.*

Similarly, Table 7 shows that listeners are more likely to respond with reciprocal sharing when the stressor is more common, and thus more frequently experienced by others regardless of their occupational contexts. For example, the probability of reciprocal sharing was positively related to concerns about viability of quitting ($b = .17$, $p < .001$), HR/management-related issues ($b = .08$, $p < .05$), scheduling mismanagement ($b = .11$, $p < .01$), work-family conflict ($b = .63$, $p < .001$), and disrespectful workplace environment ($b = .13$, $p < .01$).

Conversely, we found that stressors that manifest uniquely in specific occupational settings were met with less reciprocal sharing, such as essential work concerns ($b = -.13$, $p < .001$), field-specific nursing concerns ($b = -.42$, $p < .001$), inadequacy of compensation and benefits ($b = -.21$, $p < .001$), and unemployment assistance issues ($b = -.12$, $p < .001$). Occupational context match also seemed to play a significant role in how listeners responded to occupationally-specific stressors with reciprocal sharing. There were significant interactions between the occupational match variable and essential worker concerns ($b = .11$, $p < .01$), field-specific nursing concerns ($b = .73$, $p < .001$), field-specific postal work concerns ($b = .09$, $p < .05$), and field-specific teaching concerns ($b = .12$, $p < .05$), as well as inadequacy of compensation and benefits ($b = .14$, $p < .001$). Figure B2 includes two exemplar plots. This pattern of findings generally mirrors the interactions we observed for informational support and the theoretical rationale may be the same. That is, when listeners lack the occupation-specific knowledge and experience that is relevant to these kinds of stressors, they are less likely to try to provide guidance through the lens of their own experiences. Putting these findings together, we propose:

P3. Listeners *are less (vs. more) likely to respond to types of stressors that are (are not) occupationally specific with reciprocal sharing.*

P4. The relationship between occupationally-specific stressors and reciprocal sharing varies depending on the occupational context match of the listener, such that a match mitigates the negative relationship between these stressors and reciprocal sharing.

3.3 | Relationship between social coping behaviors and listener responses

Next, we examine the relationship between the sharer's social coping behavior (i.e., informational support seeking and/or emotional social sharing) and the listener's response. Informational support seeking was positively related to received informational support ($b = .18$, $p < .001$) and reciprocal sharing ($b = .26$, $p < .001$), but was negatively related to positive socioemotional support ($b = -.08$, $p < .001$). Taken together, this suggests that explicitly seeking information signals to listeners that the sharer has a deficit of information and does not need to be comforted. As such, we propose:

P5. Listeners are more likely to respond to informational support seeking with (a) information and (b) reciprocal sharing, and (c) they are less likely to respond with positive socioemotional support.

The effects of emotional social sharing are a bit more complex and depend on the discrete emotion (i.e., anger, sadness, and fear) that is being expressed. One pattern that emerged is related to the grouping of more cognitive-oriented responses noted above (i.e., informational support, reciprocal sharing, and reframing). The results suggest that sharing of anger is less likely to elicit these more cognitive-oriented responses ($b_{information} = -.18$, $p < .001$; $b_{reciprocal} = -.17$, $p < .001$; $b_{reframing} = -.09$, $p < .001$), but that sharing of fear is more likely to elicit them ($b_{information} = .04$, $p < .001$; $b_{reciprocal} = .08$, $p < .05$; $b_{reframing} = .10$, $p < .001$). One explanation for this may be that anger is associated with appraisals of high certainty, whereas fear is associated with appraisals of low certainty (Smith & Ellsworth, 1985). According to social functional accounts of emotion (Frijda, 1986; van Kleef, 2009), emotional expressions may provide cues regarding the expresser's underlying motivational state. Thus, listeners may infer from the expression of anger that the sharer is more certain about the issue they are facing and may be less likely to change their mind, which explains a reduction in the use of these more cognitive responses that may change the way the person thinks or behaves. Conversely, fear signals that the person is quite uncertain and thus may be more accepting of information, advice in the form of personal stories, and attempts to reframe one's appraisals. Sadness is more moderate in terms of the certainty appraisals it conveys, which would explain why the effects for that expressed emotion are generally weaker. We propose the following:

P6. Listeners are (a) less likely to respond to emotions characterized by high certainty appraisals (e.g., anger) and (b) more likely to respond to emotions characterized by low certainty appraisals (e.g., fear) with cognitive oriented responses (e.g., informational support, reciprocal sharing, and reframing).

Expressed anger was also negatively associated with positive socioemotional support ($b = -.03$, $p < .01$), whereas both sadness ($b = .02$, $p < .05$) and fear ($b = .03$, $p < .05$) were positively related to it. Sadness and fear are both withdrawal-oriented emotions and signal a desire for warmth and positive emotional support from others, whereas anger is more approach-oriented and does not signal a desire for emotional connection (Scherer, 1997). Again, drawing from social functional accounts of emotional expression (e.g., Frijda, 1986; van Kleef, 2009), this pattern of results could be because the listener is inferring these desires and responding in kind. As such:

P7. Listeners are more likely to respond to withdrawal-oriented emotions (e.g., sadness and fear), but less likely to respond to approach-oriented emotions (e.g., anger) with forms of positive socioemotional support.

Another interesting pattern that we identified for anger is that it is positively related to both negative socioemotional support ($b = .13$, $p < .001$) and opposition ($b = .04$, $p < .001$). This might be due to the highly contagious nature of expressed anger (Barsade et al., 2018), which may cause the listeners to also experience more anger and provide these two more negatively-valenced responses. Given that anger is an other-focused and confrontational emotion, it may also lead the listener to "take a side," either in support of the sharer (in the case of negative socioemotional support) or in support of the target of the sharer's anger (in the case of opposition), depending on how the listener appraises the anger-inducing situation (Mitchell et al., 2015). The positive effect on opposition was further strengthened when there was an occupational-context match ($b = .02$, $p < .001$; see Figure B3 for a plot of this interaction). Extant research suggests that emotional contagion occurs more readily between those who share salient characteristics (Gump & Kulik, 1997), which might explain this interactive relationship, though occupational context match did not moderate the relationship between anger and negative socioemotional support. We propose the following and also suggest that future research explores the role of occupational similarity in these kinds of contagion effects.

P8. Listeners are *more likely to respond to vented anger with (a) more negative socioemotional support and (b) more opposition.*

Finally, we observed that occupational context match strongly moderated a number of relationships between expressed fear and responses in a consistent way, whereas the effects were much weaker for expressions of anger and sadness. For example, occupational context match moderated the effects of expressed fear on positive ($b = .09$, $p < .001$) and negative socioemotional support ($b = .10$, $p < .001$), reciprocal sharing ($b = .21$, $p < .001$), and reframing ($b = .08$, $p < .001$). The plots for reciprocal sharing and reframing found in Figure B4 provide good examples of the nature of these interactions. It seems that the occupational context match plays a greater role in increasing the supportive responses to fear compared to responses to anger or sadness. One explanation for this may be that fear is an emotion that is oriented toward situations (Lerner & Keltner, 2001) and these are situations that may be more familiar to those with an occupational context match, triggering a greater sense of empathy and ultimately a stronger supportive response aimed at reducing the fear.

P9. Occupational context match increases the likelihood that listeners will respond in ways intended to reduce fear through greater state empathy.

3.4 | Research Question 3

The final research question focused on how sharers reacted to listener responses. To examine these relationships, we ran multi-level regressions of affective reactions reflected in the posts (i.e., satisfaction, anger, sadness, and fear reflected in the sharer's subsequent posts in the conversation) on (a) the control variables (i.e., all 18 stressors and the response's score (total upvotes-total downvotes)[3], (b) listener responses (informational support, positive socioemotional support, negative socioemotional support, opposition, reciprocal sharing, and reframing), (c) the social coping behaviors (i.e., informational support seeking and the shared emotions of anger, sadness, and fear), and (d) the interactions between listener responses and social coping behaviors. We present the full regression results in Table 8.

First, we observed a pattern for informational support seeking such that the positive relationship between informational support seeking and subsequent satisfaction is enhanced when positive socioemotional support is received ($b = .65$, $p < .001$) and when reframing is received ($b = 1.11$ $p < .001$; see Figure B5 for a plot of these results). This may indicate that while the sharers are signaling through their communication that they simply want tangible advice or information (given that the expression of emotions is controlled in the model), they are likely appraising the situations they face as threatening, and so they appreciate expressions of goodwill and empathy as well as attempts to get them to appraise the problem differently. It should also be noted that, although the findings from Research Question 1 showed that informational support seeking did encourage more reframing, it also discouraged positive emotional support. We propose:

> *P10*. Listener *attempts to improve sharer well-being through positive socio-emotional support and reframing are particularly effective in response to solicitations of informational support.*

Turning to the effects of sharing emotions, we found that the interaction between sharing anger and receiving informational support on the subsequent satisfaction of the sharer was negative ($b = -.35$, $p < .01$), though the interaction was not a significant predictor of the sharer's subsequent anger. The plot of this interaction in Figure B6 shows that the negative effect of the sharer's anger expression on satisfaction was exacerbated when they received informational support in response. One explanation for this could be related to the implications of our findings from the first research question, which is that anger is associated with an appraisal of certainty and thus receiving advice is not appreciated. In addition, given that the model also included informational support seeking as a control, information and advice received in response to the expression of anger may be construed as a form of unsolicited advice (see Landis et al., 2022), and perhaps even considered condescending. Extant research also suggests that anger reduces the likelihood that people will accept and act on the advice they receive (de Hooge et al., 2014). We propose:

> *P11. The* negative *relationship between sharing anger and reflected satisfaction is stronger when informational support is received*.

Conversely, the interaction between sharing fear and informational support is significant and positive for the sharer's satisfaction ($b = .26$, $p < .05$). As displayed in Figure B7a, the positive effect of sharing fear on satisfaction is stronger when listeners provide more informational support, perhaps suggesting that the sharer may not view this unsolicited advice as unhelpful or condescending given that fear may communicate a sense of uncertainty (Smith & Ellsworth, 1985). Interestingly, though, the interaction was also significant and positive for the subsequent expression of fear in the sharer's posts ($b = .81$, $p < .001$). Figure B7b shows that the positive relationship between the fear shared in the original post and the fear expressed in subsequent reactions is stronger when receiving informational support. One explanation for this is that, although informational support may be appreciated as a prosocial attempt to help the sharer, it might increase fear because it validates that there is a real reason to be afraid. Research suggests that fear is related to rumination and increased focus on danger (Roseman et al., 1994) and it is possible that unsolicited advice enhances the concern that something may go wrong for the sharer. This is further supported by the pattern of effects we observed for the interaction between shared fear and reciprocal sharing ($b_{satisfaction} = .23$, $p < .01$; $b_{fear} = .19$, $p < .01$), which mirror the effects shown for the interactions with informational support. Thus, we propose:

> *P12. The posi*tive effect of sharing fear on (a) satisfaction and (b) subsequent expressions of fear are enhanced when informational support is received.

> P13. The positive e*ffect of sharing fear on (a) satisfaction and (b) subsequent expressions of fear are enhanced when reciprocal sharing is received.*

The response of reframing also presented an interesting pattern when applied to emotional social sharing. Reframing did not moderate any of the effects of anger but it did moderate the effects of fear such that it enhanced the positive effect of sharing fear on satisfaction ($b = 1.41$, $p < .001$) and it weakened the positive effect of sharing fear on subsequent fear ($b = -.47$, $p < .01$). See Figure B8 for a plot of these interactions. We again draw from the certainty dimension of emotion to explain this effect. It may be that because fear is an aversive emotion related to feelings of uncertainty (Smith & Ellsworth, 1985), it is easier for others to help regulate it by encouraging one to reappraise the situation. However, for relatively more certain emotions like anger and sadness, reframing is not as effective. As such:

P14. The (a) positive effect of sharing uncertain emotions like fear on satisfaction is enhanced when reframing is received and the (b) positive effect of sharing uncertain emotions like fear on the subsequent expressions of that emotion is mitigated when reframing is received.

Finally, we noted the effects of opposition. In particular, in response to sadness, opposition actually mitigated the positive relationship between shared sadness and subsequent sadness ($b = -.42$, $p < .01$) but enhanced the effect on subsequent anger ($b = .88$, $p < .001$). See Figure B9 for plots of these interactions. This may suggest that in the online context, where one has less control over who responds and where there are weaker norms for civility, opposition can shift the emotions expressed by the sharer from sadness to anger.

P15. Opposition moderates the relationship between shared sadness and subsequent expressed anger, such that high levels of opposition increase the likelihood that one will express anger.

4 | DISCUSSION

People rely on others in their social environment to cope with work-related stressors. The literature on work-related stressors and social coping has largely overlooked the dynamic nature of the social coping process and has painted a fragmented picture of this process. To provide a more comprehensive understanding of this process, we integrated existing theories (Bavik et al., 2020; Lazarus & Folkman, 1984) to propose a three-phase process model of online social coping (see Figure 1), and used conversation-level data from Reddit to develop a theory about this process. We found that workers employ various social coping behaviors (i.e., informational support seeking and/or social sharing of discrete emotions) in this online forum to cope with a range of work-related stressors. The nature of the work-related stressors and the social coping behaviors employed by the sharer are two important sources of information, or cues, inherent in the sharers' posts that influence the type of listeners' responses. We also showed that the occupational context match can moderate the link between these cues and the listeners' responses. Finally, we found that the sharer's cues interact with the listeners' responses to alter the affective reactions the sharers reflected in their subsequent posts in the conversation.

4.1 | Theoretical contributions

We make a number of theoretical contributions to the social coping literature. First, our findings suggest that listeners respond to independent cues related to both the stressors and social coping behaviors embedded in the sharer's post and that these responses are more nuanced than the simple informational-emotional support dichotomy that is typically employed in this emerging stream of research (e.g., Luo et al., 2020; Wang et al., 2015). This further supports the notion that listener responses are not simply exogenous inputs into the social coping process (Forest et al., 2021), but are shaped in theoretically meaningful ways by cues that the sharer conveys in the post. In particular, we show that listeners independently respond to cues related to the stressor and the social coping behavior. For example, based on our findings, we propose that listeners may respond to the occupational specificity of the stressor as well as informational support seeking conveyed by the sharer with informational support and reciprocal sharing. Listeners also may respond to the certainty appraisal inherent in expressed emotion when deciding whether to provide a more cognitively-oriented response and may respond to the withdrawal-orientation inherent in the expressed emotion when deciding whether to provide positive emotional support. Finally, our findings also suggest that listener responses may be influenced by posts that contain contagious emotions like anger, which relate to the kinds of responses the listener uses.

In addition, we develop theory on the effect that listener responses have on the link between sharer social coping behaviors and affective outcomes, dovetailing with emerging research that highlights the importance of the listener's response (e.g., Baer et al., 2018; Behfar et al., 2020). Taken together with the above findings, our study suggests that social coping behaviors play the dual role of (a) directly relating to affective outcomes and (b) inviting certain listener responses, which then interact with the effect of social coping behaviors. In some cases, these two pathways worked synergistically, but in other cases, the response elicited by the sharer's cues actually harmed the affective outcome of the sharer. For example, we found that informational support seeking was more likely to encourage informational support and less likely to encourage positive emotional support, but we also found that sharers appreciated receiving positive emotional support when they were seeking information. In another example, we found that shared anger was negatively related to the provision of informational support, which turned out to be a more adaptive listener response. Additionally, our findings demonstrate that sharing fear motivated listeners to provide informational support, reciprocal sharing, and reframing. However, receiving informational support and reciprocal sharing turned out to be more maladaptive responses to that shared fear (in terms of the outcome of subsequently expressed fear), and only reframing appeared to relate to less subsequently-expressed fear. As such, our study contributes to theory on the importance of responses from the social context and how sharers can shape the responses they receive.

Finally, this study extends our theoretical understanding of the role of social coping with work-related stressors to the online context. One theoretically important distinction between the in-person and online context is that people are more likely to engage online with those from more diverse occupational backgrounds. In our sample of conversations on Reddit, we found meaningful differences in the social coping process as a function of whether the two parties shared the same occupational context or not. Although cross-occupational discussions also occur in face-to-face settings, our findings provide some theoretical clues about how the process of social coping with work-related stressors may play out online, where listeners are likely to come from a variety of occupational backgrounds, and sharers have less ability to direct their coping efforts toward similar others.

4.2 | Methodological contributions

We contribute to the emerging field of interpretive data science by enhancing the classical inductive approach through the use of ML techniques. We garnered new theoretical insights by using ML to inductively analyze big textual data collected from Reddit. We specifically used supervised and unsupervised ML, and two neural network word embedding models (Word2Vec and BERT) to convert a large unstructured corpus of textual data into meaningful categories and constructs. We evaluated the reliability and validity of these constructs by comparing the performance of these methods with each other and with human-labeled data. We also demonstrated the importance of exercising caution in creating and choosing the ground truth dataset. We did so by comparing the performance of a more powerful ML model (BERT), which was trained on an available Twitter dataset, and a less powerful tool (Word2Vec) that was trained on a training dataset created for this study using Reddit posts. This comparative process proved that the effectiveness of these ML methods can vary depending on the type and content of the data and the relevance of the ground truth dataset. Thus, scholars should use these methods, and especially the pre-trained datasets, with caution.

We also provide an example of the value and potential applications of a multi-method ML research design. In the utilization of multiple ML techniques at once, we were able to effectively retrieve and analyze big datasets for a more nuanced understanding of the dynamic, interpersonal interactions involved in the online social coping process.

4.3 | Practical contributions

This study offers organizations insight into the social coping process and may be used to develop interventions to better help employees cope with work-related stress. These interventions could be particularly targeted toward aspects of the process that seem to play out in a more maladaptive way online. To illustrate, our results suggest that when employees express their fears online, listeners may try to help the person by providing more information or by sharing their own experiences, but these responses are likely to exacerbate the fear of these employees. As such, organizations dealing with fearful employees (e.g., during an organizational change initiative) would do well to implement interventions that encourage reframing at work so that employees do not go home and share their fears online.

We also offer insights for employees in terms of how to leverage online resources for dealing with stressors to achieve their desired outcomes. For example, our results suggest that people who seek information without expressing emotions (e.g., sadness or fear) are only likely to receive informational support in response. So, to the extent that socioemotional support may be needed, one should express emotion. In addition, these insights may help employees to better respond to their coworkers' social coping attempts, which may improve workplace interpersonal relationships and employee well-being.

4.4 | Limitations and future directions

Our study has several limitations. First, our research setting is limited to online conversations on Reddit. As such, our results might not be generalizable to in-person coping. Research suggests that online interactions can be more adversarial and emotional (Crockett, 2017), though little is known about whether and how this dynamic process plays out differently with in-person interactions (McFarland & Ployhart, 2015). For instance, why do some employees choose to cope with work stressors using social media *after work* instead of sharing their problems with coworkers and supervisors *at work*? What are the organizational factors (e.g., psychological safety, organizational culture) that affect this dynamic process? Therefore, a promising avenue for future research is to develop an understanding of how online social coping is used in relation to in-person social coping and whether social coping on social media has any effects on workers' in-person social coping (e.g., Cole et al., 2017; Trepte et al., 2015).

A second potential limitation is that we were only able to model sharer outcomes as short-term affective reactions. Although we believe that these affective reactions are important, they do not directly speak to how this coping process may affect more chronic stress patterns and work outcomes. We suggest that a fruitful area for future research would be to adopt a temporal lens, which may offer insight into how the process that plays out in a single conversation affects subsequent conversations, and how these conversations over time contribute to longer-lasting effects for the person engaging in social coping.

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ENDNOTES

[1] Similar to Min et al. (2021), we found a very high correlation between anger and disgust ($r = .93$). The correlation between disgust and anger was relatively high ($r = .46$) when using the Word2Vec model as well. Additionally, we repeated all the analyses reported in the results section using anger and disgust as separate variables. The direction and significance of effects were consistently similar for these two variables. Therefore, we combined the two variables in our analyses.

[2] Using *t*-tests, we compared cases when the sharer came back compared to when the sharer did not come back to the conversation and found no large or statistically significant differences between the two groups in terms of the content of the original posts (stressors and social coping behaviors) or the nature of the listener responses (see the results in Table S4 in the online supplementary document).

[3] This represents the average score (based on upvotes and downvotes) of all the responses in the conversation. We included this as a control to account for the fact that sharer reactions may also be influenced by how others reacted to a particular response in addition to the content of the response.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX A

Technical details

Unsupervised machine learning

To better understand the themes and patterns in the textual data, we used topic modeling, which is an unsupervised machine learning technique. Unlike supervised learning methods that assume a predefined set of categories into which data are classified, topic modeling is an unsupervised clustering method in machine learning used to find latent topics in unstructured textual data (DiMaggio et al., 2013; Mohr & Bogdanov, 2013). In this method, we needed to pre-process the unstructured texts and convert the documents into a document-term matrix, in which each row represented one observation in the data (in our case, one Reddit post), and columns were all the words and n-word-chains (n-grams). The resulting matrix represented the frequency (or weighted frequency) distribution of words or word-chains in the documents in the data. Different topic modeling techniques apply different statistical methods to decompose this document-term matrix and find the topics based on the co-occurrence of words/word-chains in documents (Bao & Datta, 2014; Feldman & Sanger, 2007; Grimmer & Stewart, 2013). These topics often represent underlying meanings of the group of texts that belong to that topic. As such, topic modeling is a dimension reduction method similar to PCA. Latent Dirichlet Allocation (LDA) is one of the most common and frequently-used topic modeling methods. The LDA algorithm decomposes the document-term matrix into two matrices: words per topic and topics per document. Recent topic modeling research advises against using LDA when working with shorter texts, generally less than 100 words in length (Qiang et al., 2020). Another disadvantage of LDA is that it assumes topics are independent. The average length of title and body of the posts in our data was 286 words, but because the posts in our data varied in length (19-2004 words), we believe theoretically it makes sense for various stressors to correlate, and our goal was to have a more precise understanding of the content of the data, we compared the performance of three topic modeling methods, LDA, Non-Negative Matrix Factorization (NMF), and Structural Topic Modeling (STM) in order to select the model that performed better. The main advantage of STM over LDA is that STM allows topics to correlate whereas in LDA the assumption is that the topics are independent. LDA and STM have been frequently used in the management and organizational behavior literature (Hannigan et al., 2019; Hickman et al., 2022), whereas NMF has not been as widely introduced. Next, we briefly introduce NMF.

NMF approximates the data by breaking it into its additive components (Lee & Seung, 1999). As such, NMF approximates a nonnegative matrix, A, by the product of two low-rank nonnegative matrices. Before applying NMF, we needed to prepare Matrix A by preprocessing the text documents. Unlike LDA that uses a bag-of-words model and term-frequency (Blei et al., 2003), without assigning any weights to features, in NMF, we first preprocessed the data (as we did in supervised Machine Learning), then assigned a weight to each feature. We did so by using the common weighting scheme in text-mining, term frequency–inverse document frequency (TF-IDF), which calculated how important a feature was to a document in a collection of documents (Feldman & Sanger, 2007). TF-IDF gives the feature *w* in document *d* the weight TF-IDF:

$$TF - IDF\ Weight\,(w, d) = TF\,(w, d) \times log\left(\frac{m}{df\,(w)}\right)$$

where $TF(w, d)$ is the frequency of the feature *w* in document *d*, *m* is the number of documents, and $df(w)$ is the number of documents containing the feature *w*. We converted the documents to a high dimensional sparse matrix $A_{m\times n}$, where *m* was the number of all documents in the data and *n* was the number of all features(*terms*). Depending on the model, each *term* can contain one word or/and a chain of n words (n-grams). In this study we used 1–2 grams.

In topic modeling, similar to PCA, we needed to decide on the number of topics (k) in advance. The goal of NMF was to find the two matrices *W* and *H* with only nonnegative entries such that $A = W \times H$. The matrices W and H are found by solving an optimization problem defined as the minimization of the distance between *A* and $W \times H$ using the Frobenius norm (Kuang et al., 2015). The model generated summaries of topics in terms of weight distribution over words for each topic and weight distribution of each document over topics.

Word Embedding

In this study we mainly used Word2Vec (Mikolov et al., 2013), a word embedding model, to measure how much the texts were similar to certain concepts of interest. Word2Vec models use shallow neural networks to convert words to numerical lower-dimensional vector spaces, such that words with similar meanings are closer to each other in the vector space (Mikolov et al., 2013). This method is an improvement over the bag-of-words approach that results in sparse vectors. Sparse vectors mainly describe the documents but do not approximate the meaning of words (Mikolov et al., 2013).

We used Google's pre-trained model (Google, 2013), which was trained on Google news data (about 100 billion words) and contains 3 million words and their associated 300-dimensional vectors (Mikolov et al., 2013). To do so, first, we preprocessed the documents as explained before. Then, we constructed an $N{\times}M$ document-term matrix, T, using TF-IDF features, where N was the number of documents in the data and M was the number of terms in the data. Using Word2Vec, we also created an $M{\times}300$ matrix, W, that mapped each term in the document to a 300-dimensional vector. By multiplying these two matrices, we got an $N{\times}300$ matrix, D, that represents the N documents in the data in a 300-dimensional vector format.

$$T_{N\times M} \times W_{M\times 300} = D_{N\times 300}$$

To measure emotions (either the expressed emotions in the original posts or reflected emotions in the sharers' reactions to the responses they received), we averaged the vectors for the word and some of its close synonyms for each of the four basic negative emotions (anger, disgust, sadness, and fear) using the Word2Vec model, and then subtracted the vectors for the opposite emotions from the average. For anger, we averaged vectors for "angry," "frustrated," and "annoyed." For disgust, we averaged vectors for "disgusted" and "appalled." For sadness we averaged vectors for "sad" and "depressed." For fear we averaged vectors for "fearful," "anxious," "worried," and "scared."

We also measured these emotions using BERT, a deep learning transformer model (BERT; Devlin et al., 2019). BERT is basically a word-embedding model, but its bidirectional nature allows it to consider previous and subsequent words simultaneously, which provides a richer embedding of words in the context of the document. Min et al. (2021) used BERT to measure the basic emotions including anger, disgust, fear, and sadness in tweets about working from home during the COVID-19 pandemic. We followed the steps and code provided in that paper to measure the basic negative emotions. As in Min et al. (2021), we first used a pre-trained BERT model that contextually encodes words into vectors. We then fine-tuned the model using another pre-trained dataset (Mohammad et al., 2018) also used by Min et al. (2021). Fine-tuning is an important step that aligns the BERT model with the labels of interest that exist in the fine-tuning training dataset. The fine-tuning dataset (Mohammad et al., 2018) was a sample of manually classified tweets into six main emotions (anger, disgust, sadness, fear, joy, and surprise). We used negative emotions and fine-tuned our BERT model by adding four output layers, one for each emotion, to the BERT layers. These layers led the model to classify whether a post displayed that respective emotion or not. Thus, BERT classified the input (posts) into those four classes (1 if the text reflects that emotion and 0 otherwise). When we calculated the accuracy of the algorithm using the fine-tuning dataset, the accuracy was 89% on average for the four negative emotions. However, it is important to note that this metric did not tell us anything about the quality of prediction in our dataset.

Augmenting supervised machine learning with word embedding

In classifying responses, we compared the performance of three models (a) supervised machine learning, (b) word-embedding, (c) supervised machine learning augmented with word embedding.

In the first model, we applied supervised machine learning to the labeled dataset, following the same steps we used to categorize social coping behaviors, to classify the remaining responses that were not manually labeled. We compared the performance of multiple algorithms in classifying the responses into the response categories ((a) Informational Support; (b) Positive Socioemotional Support; (c) Negative Socioemotional Support; (d) Opposition; (e) Reciprocal Sharing; and (f) Reframing). When we only used the bag-of-words approach to extract the input features, the average accuracy of the algorithms across various responses was 72% (the accuracy rate was 76% for informational support, 76% for positive socioemotional support, 69% for negative socioemotional support, 72% for opposition, 65% for reciprocal sharing, and 83% for reframing).

In the second model, we used Word2Vec to measure the extent to which the responses are conceptually close to the five target categories of classification. First, we constructed a representative vector for each concept of interest by calculating the average of vectors of the words with similar meanings, so that each concept was represented with one 300-dimensional vector.

For informational support, we calculated the average of vectors for “advise,” “suggest,” “advice,” “brainstorm,” “guidance,” and “feedback.” For positive socioemotional support, we calculated the average of vectors for “empathy,” “sympathy,” and “compassion.” For negative socioemotional support, we calculated the average of vectors for “embarrassing,” “shaming,” and “blaming.” For opposition, we calculated the average of vectors for “scolding,” “disagreeing,” and “offending.” And for reciprocal sharing we calculated the average of vectors for “griping,” “complaining,” “ranting,” and “whining.”

Next, we needed to find the similarity between the N documents ($D_{N\times300}$) and the vectors assigned to the concept (c_i, where $i \in$ {instrumental support, positive socioemotional support, negative socioemotional support, opposition, and reciprocal sharing}). To do so, we calculated the cosine similarity vector, **S** using

$$s = D_{N\times300}.{c_i}^T$$

To validate whether these features measure the concepts of interest we compared the outputs with the labeled data in the validation sample. The agreement between manual labeling and machine labeling was 70% for informational support, 78% for opposition, 62% for positive socioemotional support, 75% for negative socioemotional support, and 60% for reciprocal sharing.

Both the bag-of-words approach and the word embedding method yielded satisfactory performance but to increase the accuracy of classifications, in the third model, we decided to combine the two methods. Thus, we augmented the document-term matrix from the bag-of-words approach with the new features from word embedding and trained the algorithms using this augmented matrix of features. As an analogy, this process is similar to adding more explanatory variables to a regression model. The results of the augmented model are discussed in the manuscript.

APPENDIX B

Plots of interactions

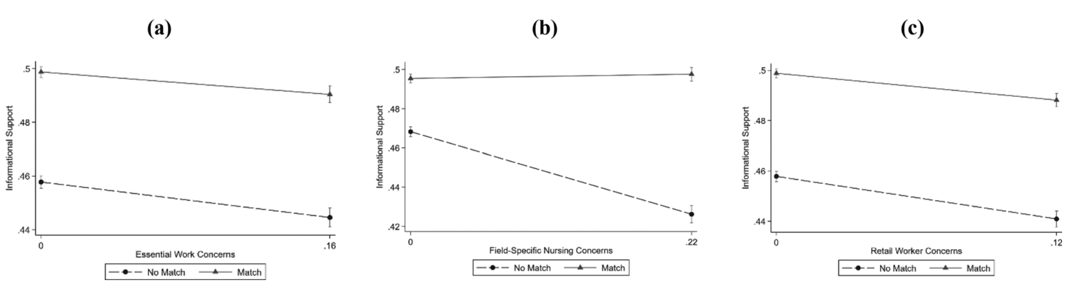


FIGURE B1 Interaction between sharer’s (a) essential work, (b) nursing, and (c) retail worker concerns and occupational context match on listener’s informational support

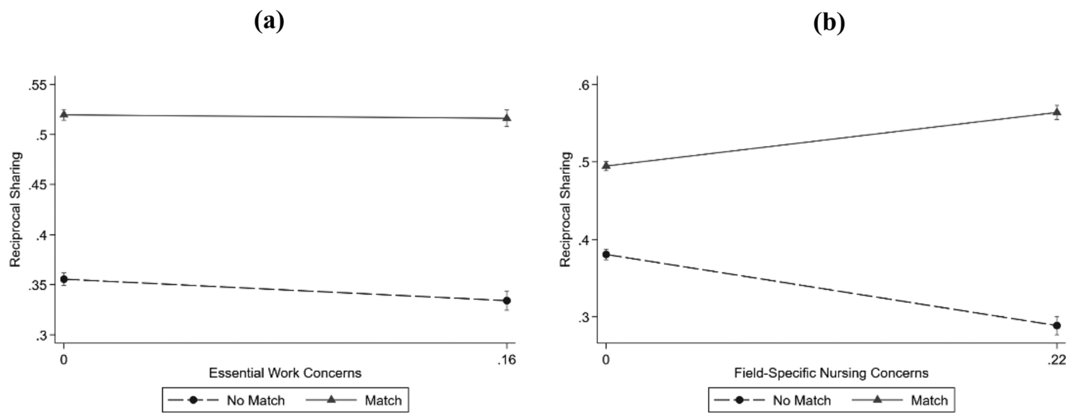


FIGURE B2 Interaction between sharer's (a) essential work concerns and (b) field-specific nursing concerns and occupational context match on Listener's Reciprocal Sharing

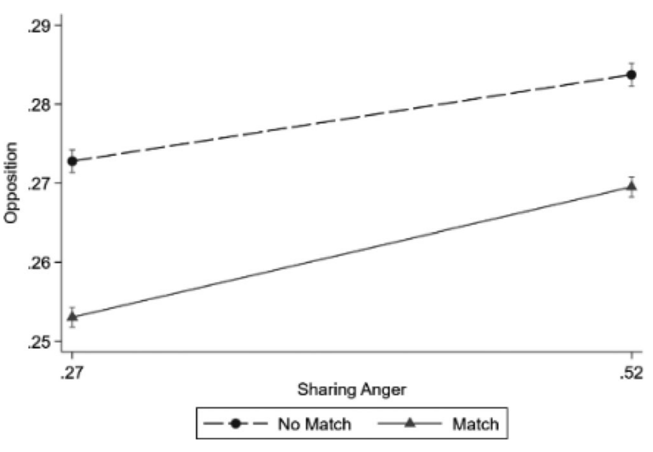


FIGURE B3 Interaction between sharer's sharing anger/disgust and occupational context match on listener's opposition

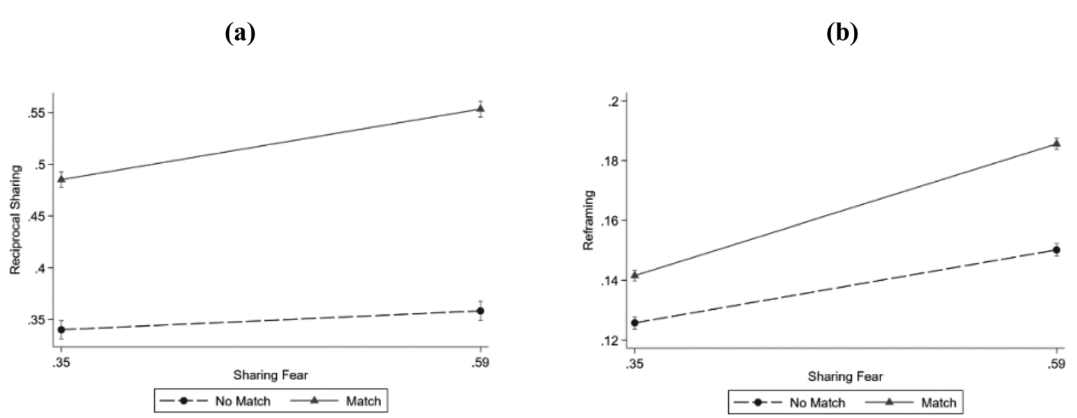


FIGURE B4 Interaction between sharer's sharing fear and occupational context match on listener's (a) reciprocal sharing, (b) reframing

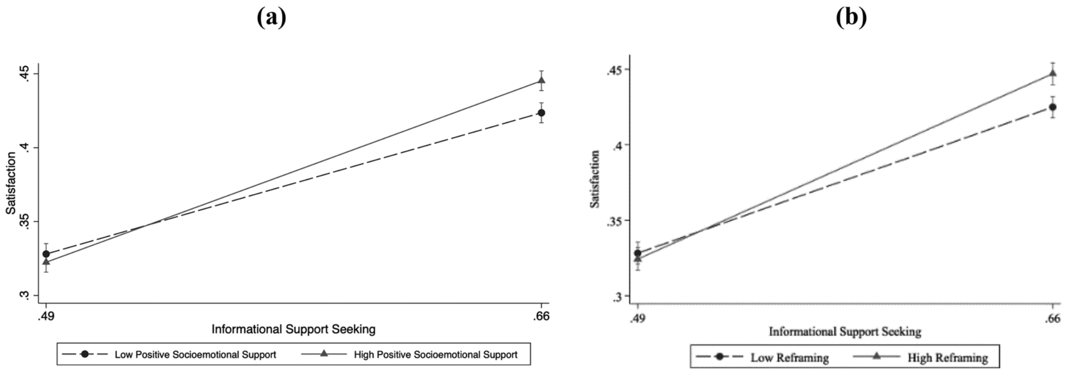
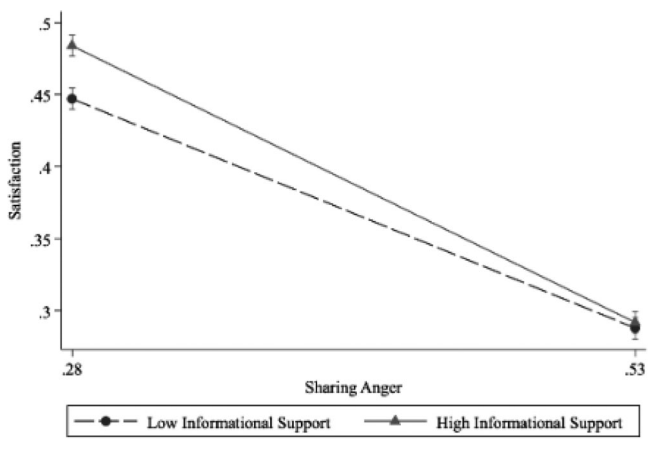


FIGURE B5 Interaction between sharer's informational support seeking and listener's (a) positive support and (b) reframing on sharer's satisfaction

FIGURE B6 Interaction between sharer's sharing anger and listener's informational support on sharer's satisfaction



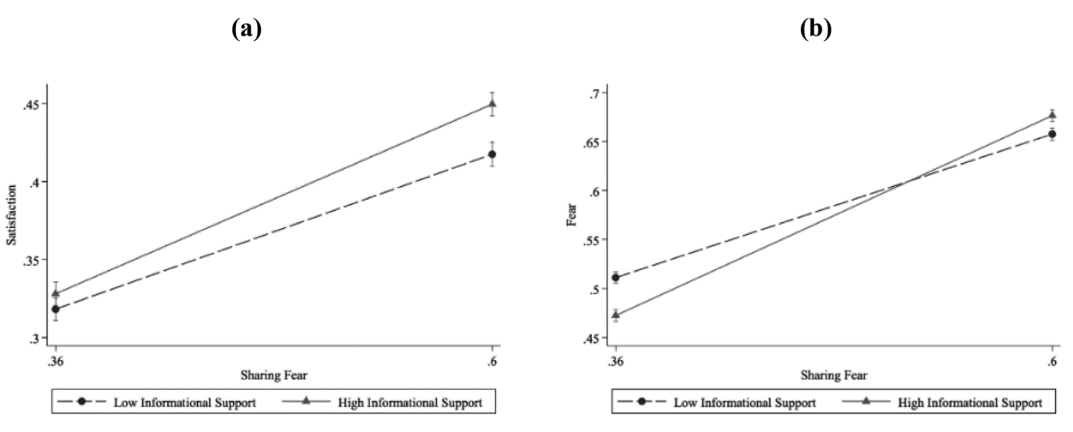


FIGURE B7 Interaction between sharer's sharing fear and listener's informational support on sharer's (a) satisfaction and (b) subsequent fear

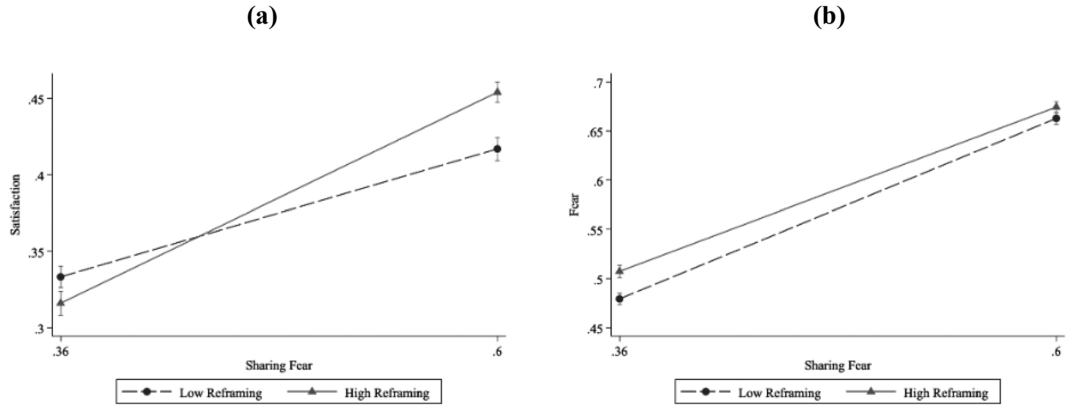


FIGURE B8 Interaction between sharer's sharing fear and listener's reframing on sharer's (a) satisfaction and (b) subsequent fear

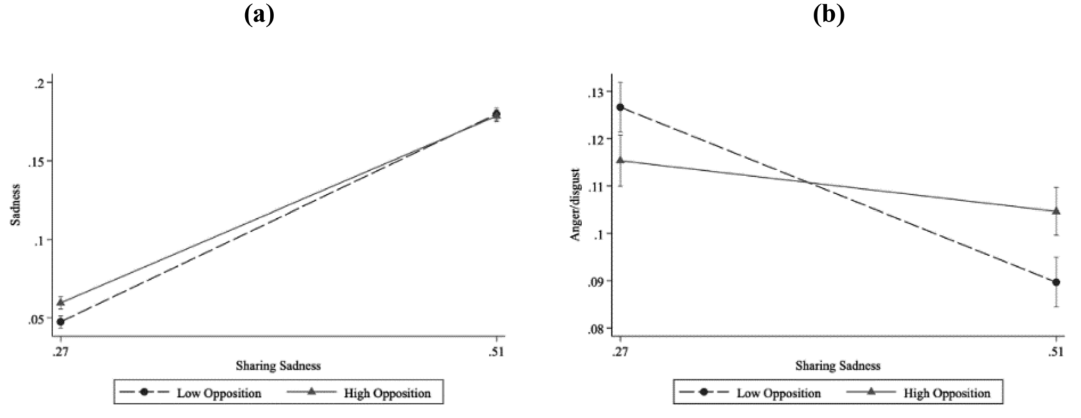


FIGURE B9 Interaction between sharer's sharing sadness and listener's opposition on sharer's (a) subsequent sadness and (b) subsequent anger