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Language Speaks Louder Than Performance: Linguistic Indicators of Cognitive Processing Across Common Threat Scenarios

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ABSTRACT

Psychological theories suggest that threat universally suppresses analytical reasoning by triggering intuitive, emotionally driven responses. We conducted a large-scale experiment ($N = 2708$) to compare the effects of 11 threat manipulations on cognitive performance and linguistic expression. Using behavioral tasks and linguistic analysis, we found threats did not significantly impair cognitive performance; they did affect linguistic indicators of analytical thinking, emotional expression, and social orientation. For example, exposure to the climate change scenario increased analytical language use, whereas exposure to pathogen-related threats decreased it. Network analyses of participants' written responses revealed distinct clusters of cognitive, affective, motivational, and social language, with affiliative terms emerging as central across most conditions. This suggests linguistic markers may capture variations in cognitive framing under stress that are not detectable in performance tasks. These findings challenge one-size-fits-all models of threat and emphasize the importance of understanding how people reason and regulate their emotions across common threat scenarios.

1 | Introduction

Threat is a fundamental element of human experience, influencing cognition, emotion, and behavior in diverse ways. Threats can be ecological (e.g., climate change, scarcity of resources, pathogens), social (e.g., migration, terrorism), relational (e.g., separation, mistrust), or existential (e.g., mortality), and they are not merely individual stressors across these forms; rather, they represent complex situations that require adaptive cognitive responses, decision-making processes, and communication. However, psychological research on threat has traditionally focused on a narrow subset of threat types, often under the assumption that threats universally induce intuitive or heuristic-based thinking while suppressing analytic reasoning. For instance, studies employing mortality salience (Greenberg et al. 1990; Pyszczynski et al. 2004) and terror-related cues have frequently concluded that such manipulations prompt intuitive responses, consistent with dual-process accounts of cognition (Trémolière et al. 2012, 2014; Yilmaz and Bahçekapili 2018). Another type of threat, resource scarcity, has been similarly shown to impair cognitive performance, presumably by diverting attentional resources (Mani et al. 2013). These findings have helped establish the idea that threat broadly undermines analytic processing.

Yet, recent theoretical and empirical developments challenge the assumption of a uniform psychological response to threat. A growing body of work suggests that different threats may elicit qualitatively different cognitive responses. Civai et al. (2024) reviewed evidence suggesting that while scarcity often impairs cognitive performance by increasing cognitive load (e.g., Mani et al. 2020), under certain motivational conditions, individuals may adaptively reallocate cognitive effort—especially when resolving resource-related problems is perceived as urgent or socially reinforced. From an applied perspective, cognitive flexibility may determine how effectively people reason and make decisions in uncertain or high-stakes everyday situations, such as when responding to health warnings or financial risks. In a similar vein, studies grounded in the Issue Ownership Model (Goren 2005; Landau-Wells and Saxe 2020) demonstrated that threats stereotypically associated with liberal political leadership (such as climate change or corporate misconduct) can lead individuals to adopt more liberal policy preferences, contrary to theories predicting a general conservative shift under threat (Eadeh and Chang 2020).

Moreover, not all threats are psychologically proximate or emotionally vivid. Some—like climate change or global migration—are temporally distant and abstract, and may thus promote analytical or future-oriented reasoning rather than triggering intuitive responses. Drawing on construal level theory (Trope and Liberman 2010), these threats may activate higher-level, systematic cognition rather than low-level heuristic processing. Other categories of threat, such as separations or existential concerns, have distinct implications: belonging and social identity are undermined by relational threats, while worldview protection and symbolic defenses are evoked by existential threats (e.g., mortality salience). Accordingly, it is conceptually inadequate to treat all threats as psychologically interchangeable or assume homogeneity in their cognitive effects. Taking a more applied cognitive approach requires examining how individuals interpret and reason about threats that vary in terms of their immediacy, controllability, and relevance to everyday decision-making.

A critical obstacle to advancing this theoretical refinement is the lack of methodological standardization in threat research. Most studies rely on idiosyncratic manipulations—videos, images, or text-based prompts—without systematic validation. Replication efforts for even widely used manipulations such as mortality salience or scarcity have been inconsistent (O'Donnell et al. 2021; Sætrevik and Sjåstad 2020), casting doubt on their robustness. Furthermore, the field lacks a unified experimental framework that enables the comparison of different threat types using consistent procedures and outcome measures. Such standardization is also crucial for applied cognitive research because the goal is to link controlled experimentation with performance and communication in natural settings.

Compounding this issue is the limited sensitivity of commonly used dependent variables. As Maxwell et al. (2015) noted, even valid manipulations can appear ineffective if measured by blunt instruments. While behavioral tasks such as cognitive reflection tests or memory recall have their merits, they may overlook subtler psychological shifts. For instance, individuals may downregulate their emotional expression or adopt context-sensitive reasoning strategies that are not easily detected using performance-based measures alone. Linguistic analysis offers a promising complementary approach. Recent work on language-based assessment shows that open-ended text can capture psychologically meaningful states (e.g., well-being) and appraisals in a context-rich way, complementing closed-ended measures and performance tasks (Mesquiti et al. 2026). Specifically, linguistic responses naturally reveal how people perceive, express, and address threats, whether they are ecological, social, relational, or existential (Ireland and Pennebaker 2010). Language offers a distinctive perspective on cognition because it reflects how individuals reason, plan, and communicate when solving everyday problems. Tools such as Linguistic Inquiry and Word Count (LIWC; Boyd et al. 2022) can quantify analytical versus emotional language in participants' written responses, offering a naturalistic window into their cognitive styles under different threat conditions. Incorporating such diverse methods allows researchers to detect psychological shifts that precede or accompany exact behavior, offering a more nuanced understanding of responses to threat (e.g., Ireland and Pennebaker 2010; Pennebaker et al. 2014). In this study, we focused more on the stylistic and functional dimensions of language (e.g., analytic thinking, cognitive processes, affective processes, and social orientation) rather than modeling semantic content or thematic similarity. We selected these dimensions because prior work links analytic language to systematic reasoning, cognitive process words to reflective thinking, affective language to emotion regulation, and social language to affiliation and identity processes under stress (e.g., Pennebaker et al. 2003). More importantly, these dimensions correspond to established models of cognitive appraisal and stress response, in which threat processing involves meaning-making, emotional activation and regulation, and shifts in social positioning (Lazarus and Folkman 1984; Smith and Ellsworth 1985). Consistent with recent work on language-based psychological assessment, these interpretable markers offer a theory-linked way to quantify how people appraise and communicate about complex experiences in everyday contexts.

Although embedding-based approaches (e.g., distributed semantic representations) also provide powerful tools for modeling semantic similarity and contextual meaning (Garten et al. 2018), they are less directly aligned with our focus on stylistic indicators of cognitive processing. Accordingly, we focused on psychologically defined language categories (e.g., analytic thinking, affective processes, social orientation) that allow for direct examination of cognitive processing styles across conditions. In this context, LIWC provided a theory-consistent and interpretable framework aligned with our analytic objectives.

Building on this rationale, the present study employed a large-scale, preregistered experimental design to systematically compare 11 threat manipulations, including climate change, scarcity (economic and environmental), health threats, mortality, war, and terrorism, against both active and passive controls. In line with our preregistration (https://osf.io/skj76/?view_only=89662426cf2d4e90b45275d4839fab77), we tested confirmatory hypotheses concerning the effects of threat on cognitive performance. In contrast, our linguistic analyses were exploratory and aimed to map how different threat types are reflected in interpretable stylistic dimensions of language, rather than to test strong directional predictions for each category. By analyzing both behavioral measures of cognitive performance and linguistic responses, we provide a comprehensive evaluation of how different threats affect perceived threat, analytical reasoning, and emotional expression. By doing so, we expand threat research into applied cognitive domains. This demonstrates how natural language reveals patterns of reasoning and communication that are relevant to decision-making, education, and the public's understanding of risk. To our knowledge, this is the first study to examine such a broad range of threat types within a unified methodological framework.

2 | Method

2.1 | Participants

We conducted an a priori power analysis to determine the required sample size for our main analysis, MANOVA. To detect a small effect size ($f = 0.10$) with 95% power, we estimated a required minimum sample of 2597 participants. Based on this, we recruited 3059 participants from the United States via Prolific and stratified them by age, sex, and political affiliation. The final sample included 2708 participants. The reduction in sample size was due to participants who only previewed the survey without completing it (75.21%), as well as those whose responses shared duplicate IP addresses (24.79%), which were excluded as potential bot activity. Among the participants, 49.93% identified as female, 48.67% as male, 1.11% as non-binary or third gender, and 0.30% preferred not to disclose their gender. Participants were aged between 18 and 95 years ($M = 45.78$, $SD = 15.90$) and were from diverse educational backgrounds: 10.08% held a high school diploma or GED, 18.06% had some college but no degree, 12.15% held an associate's or technical degree, 37.11% had a bachelor's degree, and 22.05% held a postgraduate degree. The remainder chose not to disclose their education. Annual household income was distributed as follows: 11.52% reported earning less than $25,000, 19.61% between $25,000 and $49,999, 19.65% between $50,000 and $74,999, 17.21% between $75,000 and $99,999, 19.98% between $100,000 and $149,999, and 12.04% reported earning $150,000 or more. Participants also reported their perceived socioeconomic status using the MacArthur Scale of Subjective Social Status, ranging from 1 (*lowest status*) to 10 (*highest status*). The average perceived SES was $M = 5.36$ ($SD = 1.63$). Regarding place of residence, 34.15% of participants lived in a large city, 29.93% in a small city, 22.19% in a town, 2.11% in a village, and 11.63% in a rural area. All participants were fluent English speakers and US residents at the time of data collection. This large and demographically diverse sample within the US context supports the ecological validity of the findings for real-world settings in which US residents encounter and reason about different types of threat. This study was preregistered on the Open Science Framework (OSF) before data collection (https://osf.io/skj76/?view_only=89662426cf2d4e90b45275d4839fab77).

2.2 | Measures

2.2.1 | Experimental Manipulations and Manipulation Checks

Participants were randomly assigned to one of 13 experimental conditions. Eleven conditions included the following threat manipulations: climate change, scarcity caused by climate change, scarcity caused by a financial crisis, health threat by pathogens, mortality by pathogens, separation/breakup, interpersonal mistrust, mortality, terrorism, mass migration, and war. Two conditions served as controls: an active control (involving a guided relaxation writing task) and a passive control (without any manipulation).

To reflect a broad set of threat manipulations frequently addressed in the threat and assessment literature, we selected these 11 threat scenarios. Our goal was comparative mapping across diverse, ecologically relevant threats rather than the construction of an a priori factorial taxonomy. Although we did not manipulate these dimensions (e.g., spatial or temporal proximity, chronicity, relational vs. ecological focus), our selection was based on the literature (commonly used paradigms) and was limited by the feasibility of our preregistered high-powered design. Specifically, we selected threats based on their abstractness (concrete and abstract mental representations; Trope and Liberman 2010), proximity (immediate threats and distant threats; Trope and Liberman 2010), and level of analysis (personal threats and collective or identity-related threats; Tajfel and Turner 2004; Greenberg et al. 1990), and perceived controllability (Lazarus and Folkman 1984).

Participants received a short prompt that asked them to vividly imagine the assigned scenario (e.g., *Please imagine a near future where the effects of climate change have become drastically worse.*). They then wrote four sentences describing their thoughts and feelings in response to the scenario. Immediately afterward, participants completed a series of condition-specific manipulation check items designed to assess whether the assigned threat (or control) was psychologically activated. While the manipulation check items were tailored to each specific threat condition to enhance psychological realism and relevance, all items followed a structurally identical format. Specifically, participants responded to two items: (1) "How much does the fear of [threat type] concern you?" and (2) "To what extent do concerns about [threat type] come to your mind?" Both items were rated on a 7-point Likert scale (1 = *Not at all*, 7 = *Very much*). We averaged responses to these two items to create a composite score representing perceived threat activation for each condition. This approach ensured consistent measurement across threat types while preserving semantic specificity. Given that different threats are expected to elicit unique psychological responses, we intentionally designed condition-specific but structurally parallel items, consistent with our core hypothesis that "threats are not perceived equally." Full materials, prompts, manipulation check items, anonymized raw data, and analysis scripts are publicly available on the OSF at https://osf.io/4hzyw/?view_only=9d5f1c46287549758e052dc731a020fe.

2.2.2 | Cognitive Tasks

To assess cognitive performance, participants completed two validated tasks.

2.2.2.1 | Cognitive Performance Test (CPT). To assess participants' cognitive performance, we administered a five-item CPT (Isler and Yilmaz 2023), consisting of classic cognitive reflection and probabilistic reasoning problems (Frederick 2005; Toplak et al. 2011). The first three items were the original Cognitive Reflection Test problems (i.e., the bat-and-ball problem, the machines-and-widgets problem, and the lily pads problem). Participants entered a numeric response for each question. Reflective (normatively correct) responses were coded as

1, and all other responses were coded as 0. The last two items consisted of a logical validity syllogism and a conjunction fallacy problem (see https://osf.io/4hzyw/overview?view_only=9d5f1c46287549758e052dc731a020fe for items). These two items were presented in multiple-choice format. For each item, the normatively correct (reflective) response was coded as 1 and the intuitive response was coded as 0. We summed all five items (range = 0–5), with higher scores indicating greater analytic reasoning performance. These questions capture deliberate reasoning effort, and they are extensively validated as a measure of analytic versus intuitive reasoning and shown to predict performance on reasoning, judgment, and decision-making tasks (Isler and Yilmaz 2023; Şeker et al. 2025; Toplak et al. 2011).

2.2.2.2 | Raven's Standard Progressive Matrices (SPM). Participants completed a shortened version of the SPM, a nonverbal test used to measure fluid intelligence (e.g., ability to solve new problems and identify patterns; Raven 2000). The task demonstrates strong construct validity and correlates robustly with general cognitive ability across diverse populations (Deary et al. 2010). In this task, participants looked at visual patterns and chose the piece that correctly completed each pattern. Although this task is different from the earlier writing activity, we included it to assess general cognitive ability and avoid relying only on one type of measure, which helps reduce potential bias from using a single method (e.g., common method bias).

2.2.3 | Procedure

After providing informed consent, participants were randomly assigned to one of the 13 experimental conditions. They first completed the experimental manipulation and associated writing task, followed by condition-specific manipulation check items. Next, they completed the cognitive performance measures (i.e., the CPT and the Raven's matrices). At the end of the study, participants filled out a brief demographic questionnaire including age, gender, education, income, political ideology, and subjective social status. Participants were debriefed and compensated £2.00 for their time via Prolific. Before data collection, we received ethical approval for the research from the Ethics Committee of Kadir Has University (decision number: E-82741295-600-87860).

3 | Results

3.1 | Study Overview

The results are organized into two main sections based on our preregistration plan: Confirmatory Analyses and Exploratory Analyses. Confirmatory analyses involved assessing the effectiveness of the manipulations and their influence on cognitive performance. First, to test whether our threat manipulations successfully induced a heightened sense of a specific threat, we conducted independent samples *t*-tests comparing each of the 11 threat conditions with the active and passive control conditions separately, using condition-specific perceived threat ratings as the dependent variables. Each condition included a corresponding perceived threat rating item tailored to the manipulation. For example, in the climate change condition, participants responded to the following items: (1) "How much do changes in weather patterns and their effects on your local environment concern you?" and (2) "To what extent do thoughts of environmental deterioration due to climate change come to your mind?" The wording and format were identical across conditions except for the threat topic, ensuring standardization while maintaining relevance. Second, we focused on the main effect of the threat conditions on cognitive performance measured by CPT and Raven under the confirmatory hypotheses section. More specifically, we ran a MANOVA with our 13 conditions as the levels of our IV and CPT and Raven's scores as our DVs.

In exploratory analyses, participants' written responses were linguistically analyzed using the LIWC-22 software. We conducted a series of analyses, including group comparisons and network analyses in which the contents of the texts written as part of the manipulation were used as outcome variables. In group comparisons, we compared participants' written responses to different threat manipulations in terms of basic linguistic categories (i.e., analytical thinking and emotional tone) which was calculated by the built-in dictionary of LIWC-22 (see, Boyd et al. 2022). Then, we conducted network analyses of pre-determined linguistic categories across threat conditions (see Table 1), testing whether the network pattern of linguistic categories reflected similar or different patterns. We selected these categories because they map onto core components of cognitive appraisal and stress response models, including analytic reasoning, cognitive meaning-making, affect regulation, and social positioning under threat (Lazarus and Folkman 1984). Moreover, prior work demonstrates that stylistic language markers reliably index psychological processes such as reasoning style, emotional regulation, and social orientation (Mesquiti et al. 2026; Pennebaker et al. 2003; Tausczik and Pennebaker 2009). This perspective would help us to extend our understanding of threat perception in various ways: identifying differences and similarities in linguistic structures across different threat conditions and understanding the centrality of the predetermined linguistic categories.[1]

3.2 | Manipulation Checks

We conducted separate independent samples *t*-tests, comparing each of the 11 threat conditions to the active control condition based on threat perception. Compared to the passive control group comparisons, there were not many significant differences in reports of perceived threat between those in the active control group and those in the threat condition (see Figure 1; see also Table S1 for full statistics including *t* values, *p* values,[2] and 95% CIs). All results are FDR-corrected for multiple comparisons. Specifically, participants in the Mortality by Pathogens condition reported significantly greater perceived threat compared to active control, $t = 2.70$, $p = 0.007$, $d = 0.26$, 95% CI [0.11, 0.80]. Similarly, Separation and Breakup condition participants also showed higher threat perceptions compared to active control, $t = 5.29$, $p < 0.001$, $d = 0.51$, 95% CI [0.57, 1.24]. Additionally, the War condition significantly differed from active control, indicating higher threat perceptions, $t = 2.03$, $p = 0.043$, $d = 0.20$, 95% CI [0.01, 0.66]. Other comparisons did not yield statistically significant differences (all $ps > 0.05$). Overall, the findings indicated that only three threat conditions significantly differed from the Active Control condition, whereas others (eight threat conditions) did not yield significant differences, suggesting variability in the manipulation strength across conditions as compared to Active Control.

TABLE 1 | Linguistic categories and their subcomponents derived from LIWC-22.

Linguistic component	Dimension name	Explanation	Example words	Interpretation
Insight	Cognitive processes	Words indicating understanding, reflection, or realizations.	Think, realize, know	Reflects thoughtful or introspective communication.
Cause		Words conveying causality or reasoning.	Because, effect, reason	Indicates explanation or logical connections between events.
Anxiety	Affective processes	Words expressing fear or nervousness.	Worried, afraid, nervous	Highlights emotional distress or concern.
Anger		Words reflecting hostility or frustration.	Hate, annoyed, furious	Represents aggressive or dissatisfied emotional responses.
Sadness		Words associated with sorrow or loss.	Cry, grief, lonely	Signals of emotional vulnerability or distress.
Achievement	Drives	Words related to success, effort, or ambition.	Win, goal, success	Highlights motivation and goal-oriented behavior.
Power		Words denoting dominance, influence, or status.	Control, leader, superior	Suggests a focus on authority or hierarchy.
Family	Social processes	Words referencing familial relationships.	Mom, dad, brother	Indicates communication or concerns related to the family.
Friend		Words about friendship and close non-familial relationships.	Buddy, pal, friend	Reflects focus on peer or platonic connections.
Social		Words capturing general social processes and interactions.	Talk, share, we	Broadly measures attention to social relationships and engagement.
Affiliation		Words indicating connection or collaboration	Team, ally, friend	Reflects a focus on social bonds and cooperative relationships.
Reward	Motives	Words reflecting anticipation or achievement of positive outcomes	Gain, achieve, benefit	Signals a focus on goal pursuit, success, or obtaining rewards.
Risk		Words indicating danger, loss, or avoidance of negative consequences.	Danger, fail, threat	Highlights concern for potential harm or adverse outcomes.

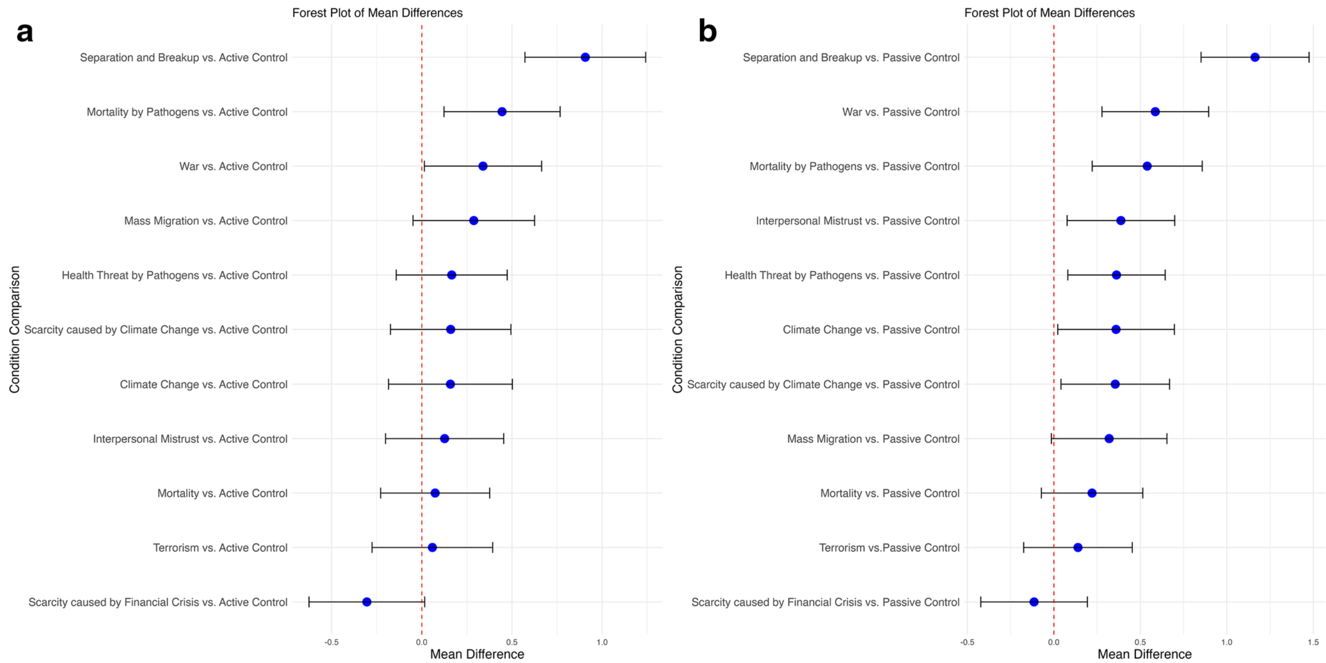

FIGURE 1 | Mean differences in perceived threat scores between each threat condition versus the passive control condition. Left panel (a) shows active control comparisons, whereas right panel (b) shows passive control comparisons. Positive values indicate higher perceived threat relative to passive control, while negative values indicate lower perceived threat. Error bars represent 95% confidence intervals (CI). Conditions whose confidence intervals do not overlap with zero (red dashed line) differ significantly from the passive control condition.

We also conducted the same set of analyses to compare each of the 11 threat conditions to the passive control condition to test whether our threat manipulations successfully induced perceived threat. As Figure 1b illustrates, analyses revealed that most threats significantly elevated the perceived threat relative to passive control. Specifically, the Separation and Breakup ($t=7.36$, $p<0.001$, $d=0.69$, 95% CI [0.85, 1.47]), War ($t=3.71$, $p<0.001$, $d=0.35$, 95% CI [0.27, 0.90]), Mortality by Pathogens ($t=3.31$, $p<0.001$, $d=0.31$, 95% CI [0.22, 0.86]), Health Threat by Pathogens ($t=2.50$, $p=0.014$, $d=0.23$, 95% CI [0.08, 0.65]), Interpersonal Mistrust ($t=2.43$, $p=0.015$, $d=0.23$, 95% CI [0.07, 0.71]), Scarcity caused by Climate Change ($t=2.12$, $p=0.027$, $d=0.20$, 95% CI [0.04, 0.65]), and Climate Change ($t=2.09$, $p=0.037$, $d=0.20$, 95% CI [0.02, 0.69]) conditions produced significantly higher perceived threat scores compared to passive control. In contrast, Mortality ($t=1.46$, $p=0.142$, $d=0.14$), Mass Migration ($t=1.86$, $p=0.062$, $d=0.17$), Terrorism ($t=0.86$, $p=0.386$, $d=0.08$), and Scarcity caused by Financial Crisis ($t=-0.72$, $p=0.470$, $d=-0.07$) conditions did not significantly differ from passive control. All confidence intervals were given in Table S1. Overall, these results showed that most threat manipulations effectively heightened participants' perceptions of that given threat, particularly threats emphasizing relational separation, existential harm, and violence, whereas economic and migratory threats were less effective.

3.3 | Confirmatory Analyses: Effect of Threat Manipulations on Cognitive Performance

To examine whether threat manipulations had a significant effect on cognitive performance, we conducted a one-way multivariate analysis of variance (MANOVA) with threat condition (e.g., breakup, climate change, mortality, etc.) as the independent variable and CPT and Raven's Progressive Matrices as the dependent variables. Before conducting the MANOVA, assumptions of normality, homogeneity of variance–covariance matrices, and multicollinearity were tested. A visual inspection of Q–Q plots yielded that the dependent variables were approximately normally distributed within each group. In addition, Box's M test was not significant (χ^2 (36) $=14.54$, $p=0.99$), suggesting that the assumption of homogeneity of covariance matrices was also met. Finally, correlations between CPT and Raven scores ($r=0.37$, $p<0.001$) were within an acceptable range, confirming no issues with multicollinearity. A one-way MANOVA showed that threat condition did not have a significant multivariate effect on cognitive performance, Wilks' $\lambda=0.99$, $F(12, 2686)=0.76$, $p=0.80$. This suggests that threat manipulations did not significantly influence cognitive test performance as measured by CPT and Raven (Figure 2 illustrates the mean differences in participants' cognitive performance scores by manipulation).

3.4 | Exploratory Analyses

3.4.1 | Comparisons of Analytical Thinking Style Across Threat Conditions

To test whether a linguistic summary component (i.e., analytical thinking) differ across various threat conditions, we ran an ANOVA. We used the scores from LIWC-22's analytical thinking category as a dependent variable which reflects the degree to which language conveys logical, formal, and hierarchical thinking. High scores indicate systematic, logical reasoning (e.g., scientific papers, technical writing), whereas low scores suggest more narrative, intuitive, or informal communication. This component is derived from the relative usage of function

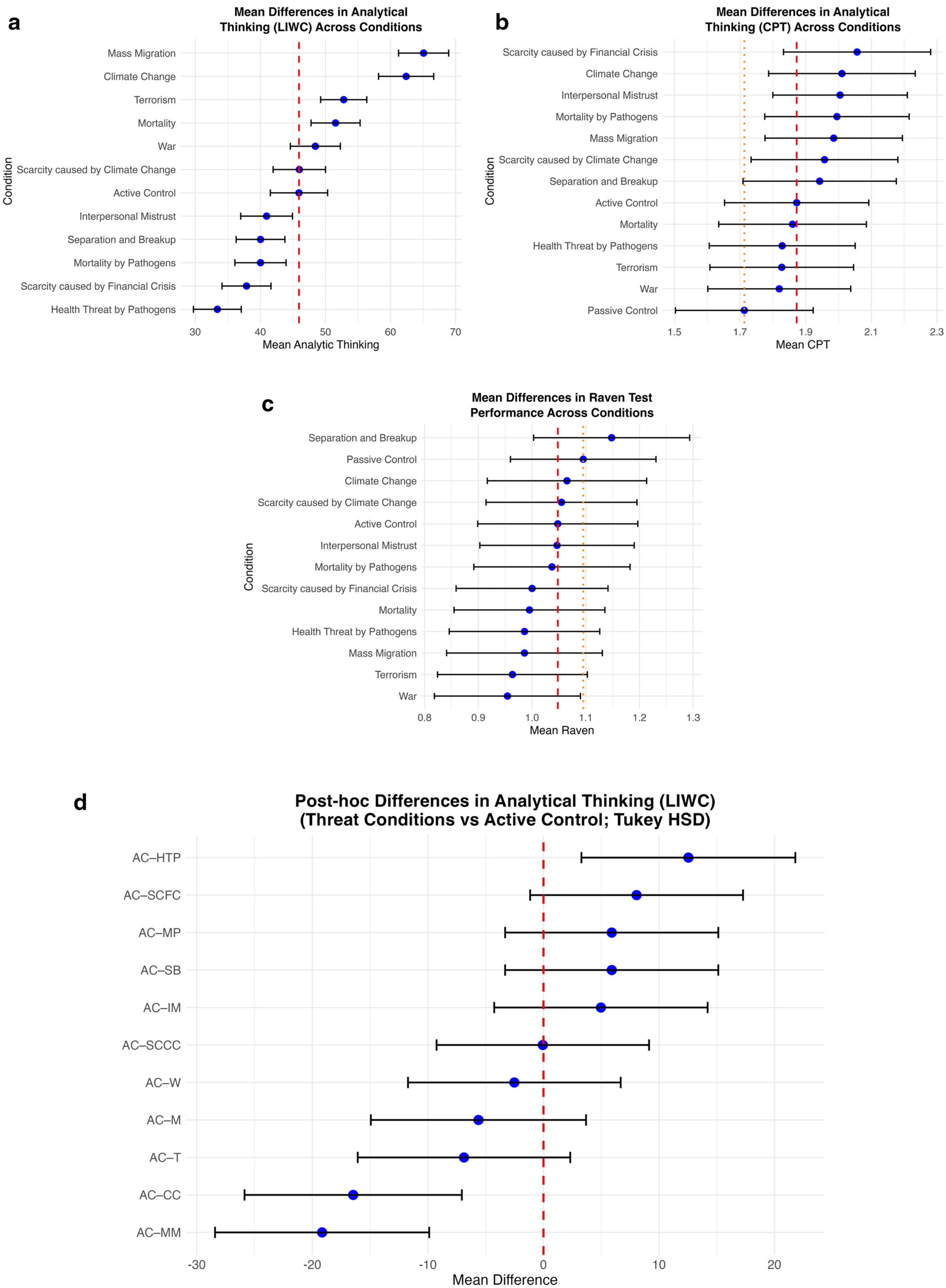

FIGURE 2 | Legend on next page.

FIGURE 2 | (a–c) Forest plots illustrating mean differences across threat conditions in terms of analytical thinking (left panel), CPT performance (right panel), and Raven test performance (below panel). Error bars represent 95% confidence intervals around the mean estimates for each condition. Because participants did not complete the writing task in Passive Control, no linguistic data are available for this condition in the analytical thinking (LIWC) panel. In the LIWC panel, the vertical dashed red line represents the mean of the active control condition. The 95% confidence intervals shown in this panel refer to pairwise comparisons of condition means and are distinct from the 90% confidence interval reported on the omnibus η^2 estimate in the main text. In the CPT and Raven panels, vertical reference lines represent the means of the active control (dashed red) and passive control (dotted orange) conditions. These reference lines facilitate interpretation of deviations from the respective control baselines. Points located further to the right indicate higher scores on the respective measures. Conditions are displayed on the *y*-axis, representing the different threat and control groups tested in the experiment. (d) Post hoc differences in analytical thinking (LIWC) between each threat condition and the active control condition (Tukey HSD). Points represent mean differences; horizontal bars indicate 95% confidence intervals. The dashed red vertical line marks zero difference. Positive values indicate higher analytical thinking relative to the active control condition. AC = active control; CC = climate change; HTP = health threat (pathogens); IM = interpersonal mistrust; M = mortality; MM = mass migration; MP = mortality (pathogens); SB = separation/breakup; SCCC = scarcity (climate change); SCFC = scarcity (financial crisis); T = terrorism; W = war. To make interpretation easier, Figure Error! Reference source not found. Shows post hoc comparisons between each threat condition and the active control condition. The full matrix of pairwise comparisons can be found in Figure S2.

words, such as articles and prepositions, that are indicative of structured thinking (see also Pennebaker et al. 2014). Scores can range from 0 (*negative*) to 100 (*positive*). Higher scores reflect more analytical thinking language, whereas lower scores indicate less analytical thinking. A one-way ANOVA revealed a significant main effect of threat condition on analytical thinking linguistic style, $F(11, 2463) = 22.08$, $p < 0.001$, $\eta^2 = 0.09$, 90% CI [0.07, 0.10] (see Figure 2a). Post hoc comparisons using Tukey's test indicated that participants in the Mass Migration and Climate Change conditions exhibited the highest levels of analytical language use, followed closely by those in the Terrorism, Mortality, and War conditions. In contrast, participants exposed to Health Threat by Pathogens and Scarcity caused by Financial Crisis demonstrated the lowest levels of analytical thinking. These findings suggest that while some threats evoked structured and logical language patterns, others may lead to more intuitive or emotional linguistic responses. The Active Control condition showed moderate analytical thinking levels, serving as a baseline for comparison (see Figure 2a). We also presented post hoc pairwise differences across threat conditions on analytical thinking separately (see Figure 2d).

3.4.2 | Networks of Linguistic Dimensions of Responses to Threat Conditions

Analyses in this section addressed three primary exploratory questions: (i) Do the selected linguistic dimensions cluster into coherent communities at the whole-sample level? (ii) Does the relational structure among linguistic categories differ across threat conditions? and (iii) Which linguistic dimensions are most central within each threat-specific network?

First, to examine whether the broad linguistic categories defined by LIWC-22 were empirically represented in our dataset, we conducted an Exploratory Graph Analysis (EGA; Atari et al. 2023).[3] As shown in Table 1, we specified four theoretically grounded higher-order domains, namely cognitive processes, affective processes, drives, and social processes. These categories were obtained from the LIWC-22 dictionary. Second, we estimated separate network analyses to see whether network structures of linguistic components were different across different threat conditions. Third, we examined the centrality indices to assess which linguistic dimensions played a structurally prominent role within each threat-specific network.

We conducted an EGA using the GLASSO model with Extended Bayesian Information Criterion [EBIC ($\gamma = 0.5$)] regularization to identify the latent structure of the linguistic categories we selected (see R codes here: https://osf.io/4hzyw/?view_only=9d5f1c46287549758e052dc731a020fe). We used the *EGAnet* package to run our analyses (Golino and Christensen 2025). The resulting network consisted of 13 nodes (i.e., linguistic categories) and 18 edges, with an overall edge density of 0.23, indicating a relatively sparse but structured network. The mean edge weight was 0.10 (SD = 0.13, range = −0.04 to 0.52), suggesting variability in the strength of connections between categories. The lambda value ($\lambda = 0.06$) indicates a moderately regularized network (see Christensen et al. 2025 for a detailed discussion of the parameters). We performed the Walktrap community detection algorithm, in which we identified four distinct clusters (see Figure 3). The first community (*C1*, *Emotion*) included insight, emotional anxiety, sadness, and anger, reflecting affective processing. The second community (*C2*, *Risk and Power*) included cause, power, and risk, representing cognitive and control-related processes. The third community (*C3*, *Achievement*) included achievement and reward, indicating goal-related motivation. The fourth community (*C4*, *Social Affiliation*) included social, affiliation, family, and friends, suggesting strong social bonding themes. The Louvain modularity algorithm (Blondel et al. 2008) indicated that the network was not unidimensional, suggesting that linguistic responses to threats were multifaceted and structured rather than a single cohesive dimension. In addition, the total entropy fit index (TEFI) = −9.17 further supported the robustness of the identified community structure (Golino et al. 2021). Overall, these findings suggest that linguistic responses to threats are organized into distinct cognitive, emotional, motivational, and social processing dimensions, with social affiliation playing a central role in shaping network structure.

Following EGA with the whole sample, we run separate network analyses across threat conditions using these distinct linguistic dimensions. Network models were estimated using the Graphical LASSO (*GLASSO*) model, with EBIC ($\gamma = 0.5$) model selection to determine the optimal sparsity of edges. As estimated in EGA, we used 13 linguistic categories: insight,

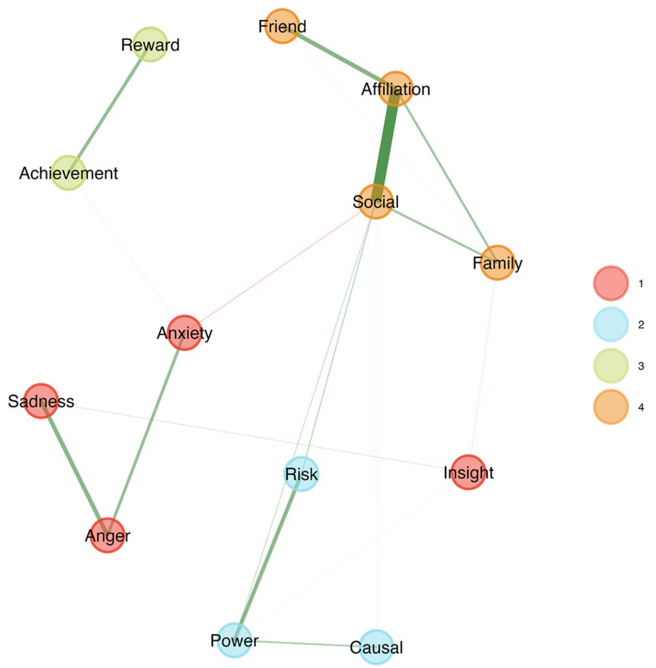

FIGURE 3 | Exploratory graph analysis of linguistic categories for all samples.

cause, emotional anxiety, emotional anger, emotional sadness, achievement, power, family, friend, social, affiliation, reward, and risk in each threat condition. The network density varied across threat conditions, suggesting that the level of connectivity between linguistic components in the networks changed depending on the threat conditions. In other words, some threat conditions have more connections between nodes, while others have fewer connections. Specifically, the density level varied from 0.13 (*Active Control*) to 0.49 (*Terrorism*). All density levels were presented in Table S3. In addition to density levels of separate network models, we also calculated communities across different threat conditions. As depicted in Figure 4 with different colors in nodes, community detection analyses revealed three distinct clusters across most conditions: (1) an emotion-focused cluster (e.g., anxiety, sadness, anger), (2) a social-focused cluster (e.g., affiliation, friend, family), and (3) a cognition-focused cluster (e.g., insight, cause). These community structures were derived from empirical partial correlation networks and were not imposed by LIWC's categorical organization. Thus, differences across threat conditions would reflect variation in the relational structure among linguistic processes rather than validation of predefined dictionary hierarchies. Moreover, some network models yielded four distinct clusters such as network models of climate change, separation and breakup, mass migration, and war. These divergent patterns based on community analyses suggested that linguistic manifestation of responses to different threats could be classified under different linguistic categories.

Focusing on the connection numbers among nodes (density) and cluster numbers (communities) would not be enough to interpret divergent patterns to different responses. Thus, we also examined the centralities of each linguistic component in different threat conditions. In other terms, this approach would allow us to examine how important each linguistic variable (e.g., insight, emotion, social terms) was within the network structure under different threat conditions. As Figure 5 illustrates, the centrality of variables varied across threat conditions. For clarity and parsimony, Figure 5 illustrates only five theoretically representative threat conditions (i.e., climate change, terrorism, mortality by pathogens, interpersonal mistrust, and the active control condition). We presented the complete set of centrality visualizations across all 12 conditions see Figure S3. The most notable finding was the centrality of social words across nearly all threat conditions (see Figures 5 and S3). Beyond these common centralities, there were some threat-specific differences in centrality scores. Specifically, reward and social-related terms had the highest betweenness centrality, particularly for climate change (*reward* = 58, *social* = 11), scarcity caused by climate change (*friend* = 45, *social* = 21), and health threat by pathogens (*social* = 29, *reward* = 24) conditions, suggesting that manifestation of responses to these threats were shown through more relational and motivational language. In terms of closeness centrality, which reflects how quickly a linguistic component connects to others in the network, cognitive and emotional-related terms tended to have higher values in terrorism (*cause* = 0.0112, *insight* = 0.0075, *sadness* = 0.0129), mass migration (*sadness* = 0.0086, *cause* = 0.0071), and war (*cause* = 0.0034) (see Figures 5 and S3 for relative differences among centrality measures). This suggests that these threats involve more integrated cognitive and emotional processing.

Finally, strength centrality, which represents the overall influence of a linguistic component within the network, was highest for motivational words (e.g., rewards [incl. gain, benefit, etc.]), particularly in climate change (*reward* = 1.9058), mortality by pathogens (*reward* = 1.3202), and scarcity caused by climate change (*reward* = 1.0542). This suggests that these threats were linguistically structured around motivational processing to minimize the threat. Another important finding on strength centrality was the importance of emotional processing, especially under proximal threats such as mortality by pathogens, scarcity caused by financial crisis, and mistrust (see Figures 5 and S3).

Overall, network analyses of linguistic responses to different threat reminders suggested that the complexity of linguistic behaviors (i.e., density), dimensions of linguistic components (i.e., communities), and the centrality of each linguistic category (centrality) varied across different threat conditions. In other words, different threats activated different linguistic and psychological processes. The following sections summarize key findings from the network density, community structure, and centrality analyses.

Network density analysis yielded some differences in the interconnection of linguistic components across 11 threat conditions. Specifically, terrorism (0.49) and mass migration (0.40) exhibited the highest network density, implying that responses to these threats were characterized by highly interconnected linguistic structures, potentially indicating a more integrated cognitive and emotional processing. In contrast, active control (0.13) and mortality (0.18) had the lowest densities, suggesting a more fragmented or loosely interconnectedness between linguistic components. Responses to other threats, such as scarcity

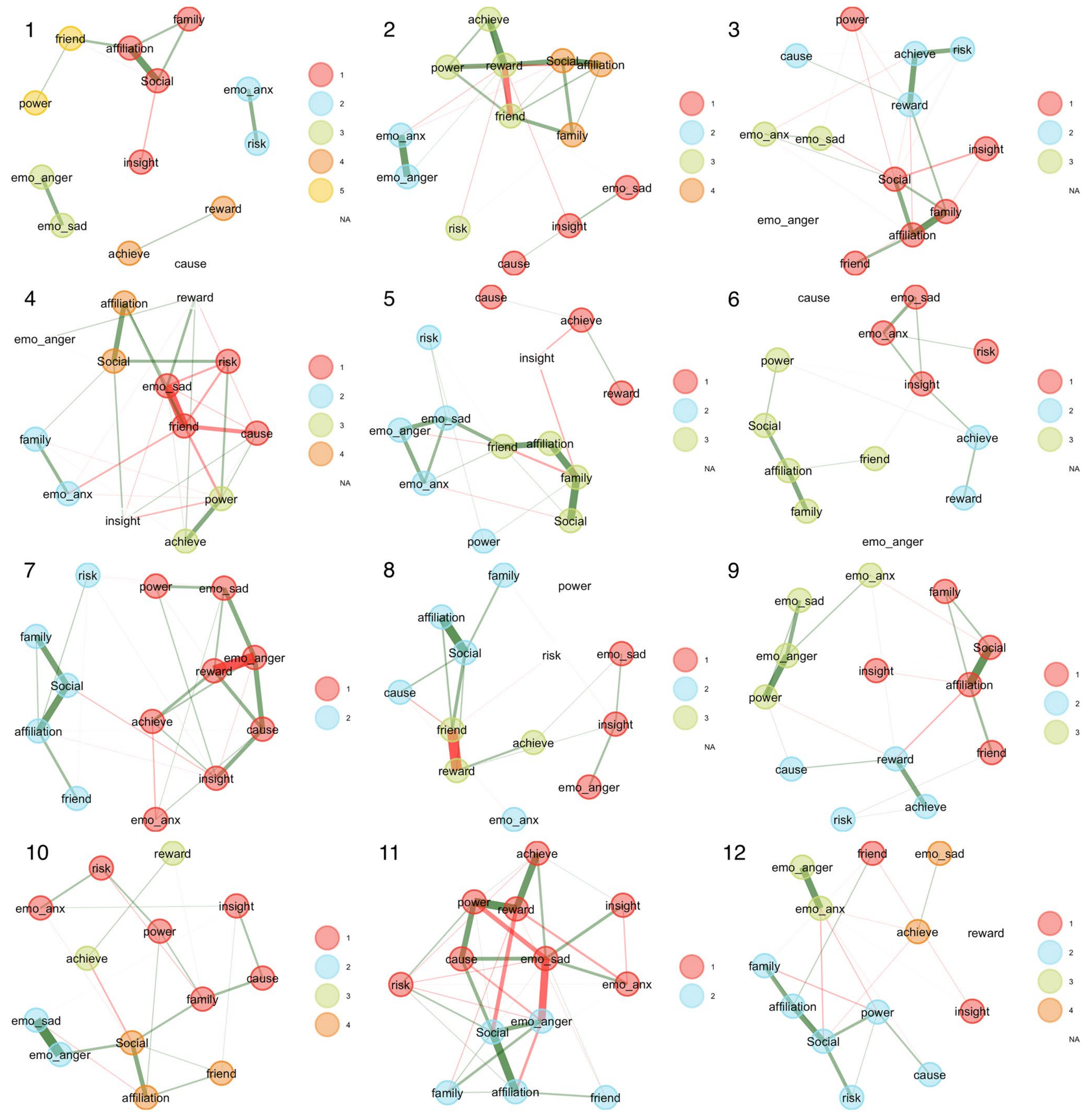

FIGURE 4 | Network models across different threat conditions. Different colors depict different clusters. *Note:* The graphs are given in the following order from left to right with each panel numbered 1–12 as follows: (1) active control; (2) climate change; (3) health threat by pathogens; (4) mass migration; (5) interpersonal mistrust; (6) mortality; (7) mortality by pathogens; (8) scarcity (climate change); (9) scarcity (financial crisis); (10) separation and breakup; (11) terrorism; (12) war. node labels use short LIWC category codes; see Figure 3 and Table 1 for the full readable labels (e.g., emo_anx = anxiety, cause = causal).

(0.27), war (0.26), and health threat by pathogens (0.31), showed relatively moderate levels of network connectivity. This implies varying degrees of complexity in the way individuals linguistically represent these threats.

Community detection analyses suggested that linguistic responses to most threats were organized into three core clusters: emotion, social, and cognition-focused categories. However, Climate Change, Separation and Breakup, Mass Migration, and War exhibited four communities, suggesting a more complex linguistic structure. In contrast, Terrorism and Mortality by Pathogens formed only two clusters, indicating a more streamlined response, while Active Control (five clusters) suggested a more fragmented linguistic representation. These results imply that different threats elicit varying levels of linguistic complexity, reflecting differences in how people cognitively and emotionally process them.

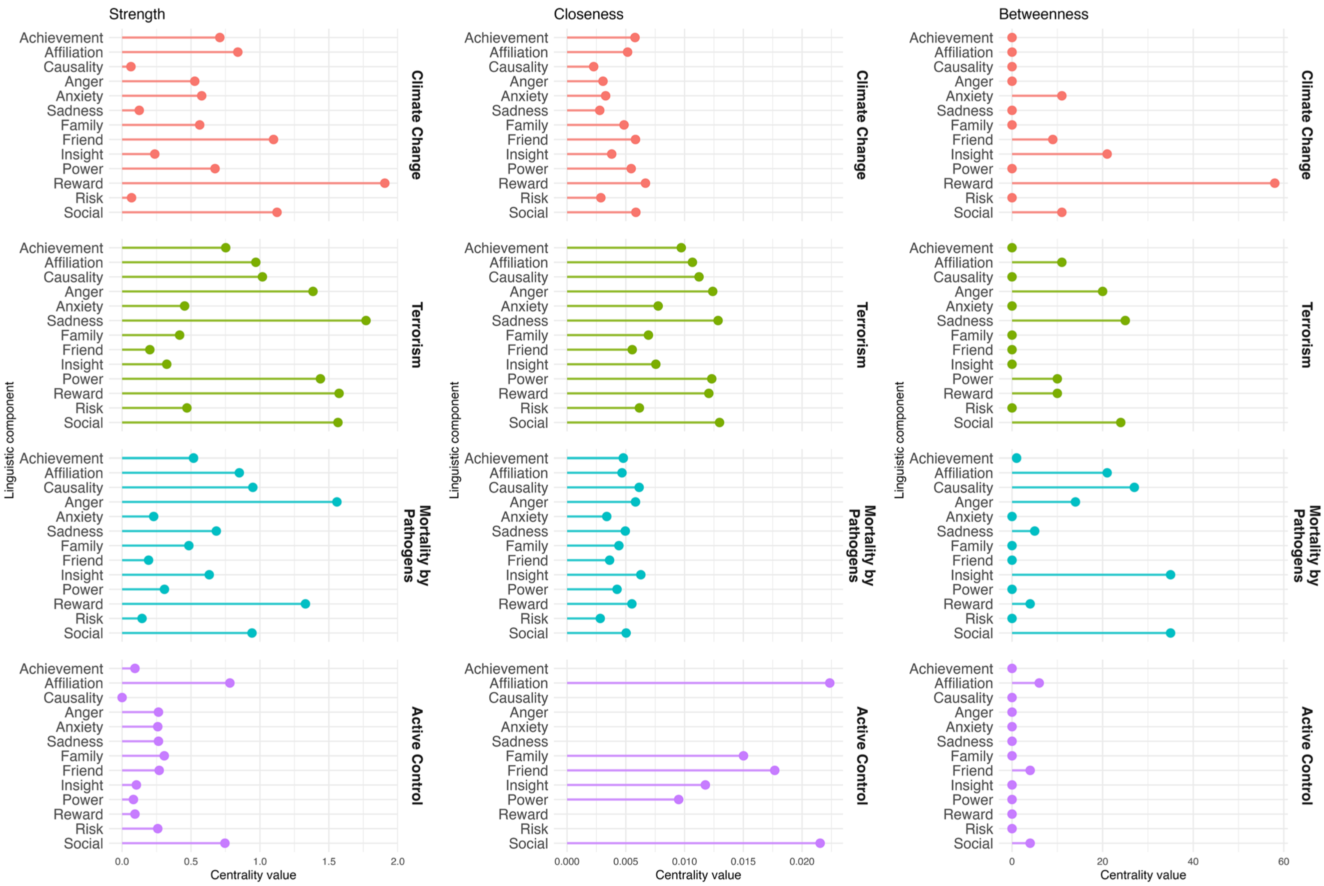

FIGURE 5 | Centrality measures of linguistic categories across five representative threat conditions (climate change, terrorism, mortality by pathogens, interpersonal mistrust, and active control). See Figure S3 for the full set of conditions.

Finally, *centrality analyses* showed that social words were central across all threat conditions, emphasizing relational processing under any kind of threat condition. Betweenness centrality was highest for reward and social terms in climate change, scarcity-related conditions, and health threats, suggesting that people engaged in a motivational mental set under these kinds of threats. In addition, closeness was strongest for cognitive and emotional terms in societal threats such as terrorism, mass migration, and war, reflecting integrated processing. Finally, strength centrality was highest for motivational words in climate change, mortality by pathogens, and scarcity-related threats, indicating a possible goal-directed response to minimize threats.

4 | Discussion

In this preregistered, high-powered study, we evaluated the psychological effects of 11 distinct threat manipulations on perceived threat, cognitive performance, and linguistic indicators of analytic thinking. Only three manipulations, Mortality by Pathogens, Separation and Breakup, and War, elicited significantly greater perceived threat than both control conditions, suggesting robust construct validity. These findings suggest that threats to personal safety, relational stability, or collective security elicit the strongest psychological responses. These domains are highly relevant to everyday thinking and communicative behavior. In contrast, some widely used manipulations (i.e., Mortality, Terrorism, Mass Migration, and Scarcity due to Financial Crisis) failed to consistently diverge from controls, indicating variability in manipulation strength across contemporary online samples.

Importantly, none of the manipulations significantly impacted actual performance on cognitive tasks (CPT and Raven's matrices), despite longstanding claims that threat impairs cognitive functioning (e.g., Trémolière et al. 2012, 2014; Yilmaz and Bahçekapili 2018). One potential explanation for the null findings of threat effects on cognitive performance may lie in the modality mismatch between the manipulation and the outcome measures. Participants were first asked to complete a written threat induction task, which was linguistically and emotionally rich, and then transitioned to abstract, non-verbal cognitive tasks such as the Raven's matrices. This shift in the task format may have disrupted the continuity of the threat activation or diluted its immediate cognitive effects. This also suggests that the cognitive consequences of threat may be context-dependent, emerging more strongly when the assessment aligns with everyday modes of reasoning, such as verbal reasoning, problem solving, and narrative reflection. Future studies could consider using more modality-congruent measures—such as verbal reasoning tasks or emotionally charged decision-making scenarios—to better capture the downstream consequences of threat induction (see also Herbert et al. 2020 for relevant evidence).

However, threat conditions systematically influenced analytical language use, as measured by LIWC-22. Although only three threat manipulations significantly exceeded both control conditions in perceived threat intensity, we retained all 11 conditions in the linguistic analyses. Perceived threat magnitude does not necessarily map directly onto linguistic processing patterns. Some scenarios may evoke moderate subjective concern yet still differ qualitatively in how individuals cognitively frame and communicate about them. Therefore, our goal was not to restrict analyses to the most intense threats, but to examine variation across a broad range of ecologically relevant manipulations.

Across conditions, Mass Migration and Climate Change conditions led to increased analytical expression, while Pathogen-related and Scarcity-related threats decreased it. This pattern suggests that more abstract or systemic threats may prompt greater cognitive elaboration and structured reasoning, whereas more immediate or survival-relevant threats may shift processing toward more experiential or affect-driven modes of expression. These findings also challenge one-size-fits-all models of threat by showing that different threat types do not uniformly suppress analytic processing; rather, they shape how individuals cognitively frame and articulate their responses. In other words, threat appears to reorganize cognitive engagement in content-specific ways rather than simply impairing reasoning.

Importantly, these differentiated effects were detectable in linguistic expression but not in behavioral performance tasks. This pattern suggests that language may serve as a particularly sensitive indicator of how individuals cognitively process, regulate, and communicate about threatening information in ecologically relevant contexts. Linguistic markers may capture shifts in psychological distancing, goal-directed framing, and affective regulation that are not reflected in abstract cognitive test performance. These linguistic shifts can be understood as cognitive traces of how individuals manage attention, reasoning, and emotional framing under uncertainty.

Further exploratory analyses (such as Language Style Matching and network modeling) revealed that different threat types generated distinct linguistic patterns. Some threats induced dense, emotionally charged language networks (e.g., Terrorism), while others resulted in fragmented or conceptually diffuse responses (e.g., Mortality). Strikingly, social-affiliative words emerged as central across nearly all networks, suggesting a universal relational response to threat. The tendency to express affiliation under stress highlights the adaptive role of language in coping and coordination. This supports the use of communication-based interventions to maintain trust and cooperation in crisis contexts. In addition to differences, terrorism and mass migration exhibited similar linguistic network structures. One possible explanation is that both scenarios involve collective-level, identity-relevant, and sociopolitical threat framing. Such threats may activate group-based cognition and intergroup considerations, leading to comparable patterns of social and affective language use.

4.1 | Implications

One theoretical implication of these findings concerns measurement sensitivity. Behavioral cognitive tasks capture outcome-level performance, whereas linguistic style reflects ongoing cognitive framing and appraisal processes. It is therefore possible that threat primarily influences how individuals construe and communicate about situations, rather than impairing core reasoning capacity per se. This distinction may reconcile prior findings suggesting threat impairs reasoning with our null performance effects.

These findings challenge the dominant view that threats uniformly elicit intuitive processing and impair analytic reasoning. Instead, our results support a differentiated model of threat effects, in which the psychological response varies by the type, proximity, and social meaning of the threat. This means that not all threats impair reasoning. Some threats may actually encourage deliberate thinking and future-oriented planning, particularly when they evoke manageable or abstract scenarios. Abstract, global threats may encourage higher-order reasoning and deliberation, whereas biologically salient threats (e.g., pathogens) prioritize survival mechanisms, reducing analytic expression.

This differentiation aligns with the Issue Ownership Model in political psychology, which proposes that individuals interpret threats through culturally embedded lenses that shape their affective and cognitive responses (Brandt et al. 2021; Eadeh and Chang 2020). For example, climate change may activate competence schemas associated with liberal ideologies and abstract reasoning, whereas disease-related threats are often theorized to evoke more immediate, survival-oriented responses (e.g., Greenberg et al. 1990; Mani et al. 2013; Trémolière et al. 2012). Such findings fit within a broader body of work suggesting that threat does not uniformly suppress analytic reasoning but can, under certain conditions, foster defensive or heuristic processing depending on how the threat is construed. Methodologically, the study advances the field by showing the superior sensitivity of linguistic measures in capturing threat responses. Linguistic indicators provide a practical, non-intrusive way to track cognitive and emotional states as they arise naturally during communication, surveys, or online interactions. Behavioral tasks did not reflect the nuanced shifts detected through written language. This discrepancy highlights the need for multimodal measurement strategies, particularly in high-variance psychological contexts such as threat, uncertainty, or affect. One potential concern is that linguistic differences across conditions may merely reflect the thematic content of the prompts (e.g., writing about war leads to war-related words), rather than genuine psychological differences induced by the threat manipulations. While the prompts varied in their thematic content to reflect specific threat domains (e.g., economic scarcity, breakup/divorce), all participants were exposed to identically structured instructions, including the same number of required sentences and linguistic task framing. This consistency across experimental conditions potentially ensured that what varied was not the form or structure of the writing task, but the psychological and affective activation induced by the threat manipulation.

An additional nuance could be the linguistic framing of some threat scenarios. Although all prompts followed an identical structural format, certain manipulations varied in perspective. For example, relational and health-related scenarios (e.g., breakup, pathogen threat) were explicitly self-referential, whereas scenarios such as climate change or mass migration were framed in broader contextual or collective terms. Such differences may partly influence pronoun usage and social language independently of threat content. Because this perspective variation was not systematically manipulated or preregistered as a focal hypothesis, we reported exploratory analyses of first-person singular and plural pronoun frequencies across conditions in the Supporting Informations. In our exploratory analyses, we found that pronoun usage varied significantly across conditions, while the pattern did not reflect a simple personal vs. collective distinction. Several threat types showed elevated levels of both singular and plural forms. This suggests that framing differences may contribute to certain linguistic shifts but cannot fully explain the broader stylistic patterns observed across threat types.

Moreover, our analytic focus was not on semantic content (i.e., topic-specific words), but on linguistic style variables derived from LIWC-22 (e.g., analytical thinking, emotional tone, use of cognitive and social processes), which are designed to abstract away from topic-specific vocabulary and instead capture how people express themselves. This allows for identifying psychologically meaningful differences in processing styles rather than simply detecting topic divergence (Pennebaker et al. 2014; Tausczik and Pennebaker 2009).

To further reduce the risk of tautological interpretation (e.g., "thinking about war leads to war-related words"), our network analytic approach examined co-occurrence structures among linguistic categories across conditions. Such patterns (e.g., the clustering of cognitive and social terms under war vs. scarcity) reflect differences in mental construal, emotional activation, and interpersonal focus rather than topicality alone. Finally, the control conditions served as critical baselines. The active control group completed the same expressive writing task but on an irrelevant topic. Comparing this control condition with threat conditions revealed that linguistic structure complexity and category centrality shifted beyond what could be attributed to mere task demands or verbosity, providing additional evidence for genuine threat-induced cognitive-affective modulation.

Practically, our results bear relevance for public messaging and political communication. Understanding which types of threats activate analytical versus emotional responses can inform educational, clinical, and policy applications. For example, it can help us design risk communications that sustain engagement without inducing panic. For instance, climate change messages could emphasize deliberation and future planning, while health communications could focus on actionable control instead of fear. From an applied cognitive perspective, language patterns offer a straightforward index of cognitive engagement that practitioners can use to evaluate how people process complex or threatening information.

4.2 | Limitations and Future Directions

Despite its strengths, the study has several limitations. First, although the sample was demographically diverse, all participants were residents of the United States. Thus, the observed patterns may reflect culturally specific ways of perceiving, communicating about, and regulating responses to threat. Second, the use of online samples, while large and diverse, may introduce variance due to environmental distractions or noncompliance. Third, although linguistic analyses offer sensitivity, they remain indirect indicators of internal cognitive states. Using a combination of linguistic markers and eye-tracking, physiological, or self-report measures could improve the effectiveness of applied assessments of attention and reasoning under threat. Fourth, we did not measure individual- and group-level moderators such as epistemic motivation, affective reactivity, or shared identity, which may influence responses to specific threat types. Future research could incorporate such moderators to develop a person-by-situation framework of threat processing.

Additionally, although our cognitive tasks were well-established, they may have lacked domain relevance for certain threats (e.g., economic scarcity). Incorporating domain-matched cognitive outcomes could yield more nuanced insights (Civai et al. 2024). Fifth, the LIWC provides interpretable and theoretically grounded indices of stylistic processing. However, it does not capture semantic similarity, contextual meaning, or phrase-level co-occurrence patterns (e.g., *n*-gram structures). Future work could combine dictionary-based and embedding-based approaches to better distinguish between thematic content and cognitive processing style under various threat types. Furthermore, we compared 11 widely used threat scenarios and these were not systematically manipulated along orthogonal dimensions (e.g., proximity or personal vs. collective focus). Future research could more openly vary such core threat features to clarify which structural aspects drive changes in cognitive and linguistic responses. Finally, we emphasize the need to explore understudied threat dimensions, including perceived controllability, agency, and norm violation. These features are likely to shape whether threats elicit disengagement, coping, or reflective processing and should be incorporated into future experimental frameworks.

5 | Conclusion

This study provides the first systematic, comparative test of how diverse threat types influence perceived threat, cognitive processing, and linguistic expression. The findings demonstrate that threat is not psychologically monolithic: it varies in salience, cognitive consequences, and expressive patterns depending on its content and perceived relevance. While traditional cognitive tasks failed to detect effects, language-based measures captured consistent and theoretically meaningful shifts, suggesting a valuable new direction for threat research. This work contributes to the applied understanding of how people think, reason, and communicate under everyday stressors by integrating linguistic analysis with cognitive performance measures. It offers possible practical tools for improving communication, learning, and decision-making in uncertain environments.

Author Contributions

Mehmet Harma: conceptualization, investigation, funding acquisition, writing – original draft, methodology, visualization, writing – review and editing, software, formal analysis, project administration,

supervision, resources, validation. **Fırat Şeker:** conceptualization, investigation, writing – original draft, writing – review and editing, methodology. **Burak Doğruyol:** conceptualization, investigation, writing – original draft, methodology, writing – review and editing. **Onurcan Yilmaz:** conceptualization, investigation, funding acquisition, writing – original draft, methodology, writing – review and editing.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are openly available in OSD at https://osf.io/4hzyw/?view_only=9d5f1c46287549758e052dc731a020fe.

Endnotes

[1] We had also another registered exploratory analysis in which we examined linguistic style matching (LSM) across different threat conditions. We reported all results for LSM in the supplementary document at https://osf.io/4hzyw/?view_only=9d5f1c46287549758e052dc731a020fe.

[2] We adjusted p values for multiple comparisons using the Benjamini–Hochberg false discovery rate (FDR) procedure.

[3] Since EGA has more flexible assumptions about the observed variables compared to EFA and CFA, we have chosen EGA to identify underlying dimensions among the series of linguistic components produced by participants. Research has also shown EGA's utility in uncovering latent dimensions by leveraging network models (Christensen and Golino 2021; Golino and Epskamp 2017).

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Table S1:** Independent samples *t*-test results comparing threat conditions with passive and active control. **Table S2:** Language style matching (LSM) scores across pairwise comparisons of threat conditions. **Table S3:** Network densities and community numbers. **Figure S1:** First-person singular and plural pronoun usage across threat conditions. **Figure S2:** Full Tukey HSD pairwise comparisons in analytical thinking (LIWC) across all threat conditions.