Understanding Uncertainty in Daily Life: Appraisals and Metacognitive Strategies

by

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A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirement for the degree of
Master of Arts
in
Psychology

Waterloo, Ontario, Canada, 2025

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

Uncertainty is an inevitable part of our lives, yet little is known about how people navigate the uncertainty they encounter in their lives. In my thesis, I examine how uncertainty is perceived, which situations are perceived as uncertain, and how people react to uncertainty in daily life, and specifically whether they engage in perspectival metacognition. To address these questions, I used data from a year-long longitudinal study asking participants ($N = 499$) to report on the most significant event of their day. Using natural language processing, I then classified these open-ended text responses as uncertain and not uncertain, and examined how participants' construal, emotional profile, and reasoning differ for uncertain compared to not uncertain events. Uncertain events were perceived as relatively more negative, challenging, in other's control, and less predictable. Uncertain events were also associated with greater negative emotion and less positive emotion. Negative event types (i.e., conflict, rejection, annoying, and sad or bad news type of events) were more likely to be classified as uncertain compared to positive or neutral event types. Participants were also relatively more likely to report intellectual humility and a search for compromise in reflections on uncertain events. These results were similar for the trait and state levels. I discuss the implications of this scholarship for research on affect and emotion regulation and on mental health, specifically for those with anxiety disorders.

Acknowledgements

I would like to thank my supervisor, Igor Grossmann for his continued support, guidance, and feedback which allowed me to expand my potential and research skills. I am grateful for the incredible things I've learned like natural language processing, complex statistical methods such as multi-level modelling, how to write like an academic, and how to think like a scientist.

I would also like to thank my readers, David Moscovitch and Sam Johnson for their detailed and thoughtful feedback. Additionally, I would like to thank Hilary Bergsieker for her excellent course teachings on Anova and Multiple Regression and Neil Hester for his course on *R* which was incredibly useful. I also cannot forget my peers and friends from social psychology for their incredible support and guidance.

Finally, I would like to thank my parents for their continued encouragement and contribution to making grad school easy for me.

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CHAPTER ONE: Introduction

Consider a situation where you are stuck in traffic and you don't know how long it's going to take to reach your destination. Imagine that you are on a dating app and you just swiped right on someone but, you are unsure if they are going to swipe right on you. Perhaps you've just applied for a job position and now you anxiously await the results from the interviewer. All these situations involve uncertainty which is an inevitable part of our daily lives. Whether you are making an important decision, navigating a life change, dealing with a chronic illness, or navigating relationships, uncertainty plays a crucial role in all situations. Uncertainty is a common and interconnected aspect of human life that has many applications and implications and spans the literature from emotion and social cognition (Ellsworth & Smith, 1988; C. A. Smith & Ellsworth, 1985; Yeo & Ong, 2024), judgment and decision-making (Kahneman & Tversky, 1982), and health-related uncertainty to clinical disorders such as anxiety (Boswell et al., 2013; Brashers et al., 2000; Carleton, 2016b), making it an important construct to study.

What is Uncertainty?

The earliest account of the concept of uncertainty was noted by the skeptical Greek and Roman philosophers who believed uncertainty to be an inevitable human condition that could not be illuminated upon through the senses nor reason. The Pyrrhonists believed that uncertainty cannot be solved by any rational means thus, it is best to just accept it as is. However, the Greek philosopher Carneades thought it was foolish to not rely on some form of reasoning or rationality to navigate uncertainty (Annas & Barnes, 2000). This thought was formalized much later in the mathematics of probability theory (Arnauld et al., 1996; Kozyreva et al., 2019).

The idea of uncertainty as probability is central to the literature from judgment and decision-making and classifies uncertainty based on the source. Epistemic or internal uncertainty

refers to uncertainty stemming from one's lack of knowledge whereas aleatory or external uncertainty stems from the environment and its indeterminacy. Uncertainty due to external events is often expressed as likelihood statements (e.g., "I think there is a 70% chance.") whereas internal uncertainty is expressed as confidence statements (e.g., "I am reasonably certain; Kahneman & Tversky, 1982; Kozyreva et al., 2019; Ülkümen et al., 2016).

Cognitive emotion theories portray a different understanding of uncertainty and emphasize *interpretation* of the event in perceiving uncertainty. According to cognitive-emotion theories, uncertainty can be defined as a lack of understanding of what is happening and not being able to predict what will happen in the future (C. A. Smith & Ellsworth, 1985; Yeo & Ong, 2024). Uncertainty is an appraisal dimension that predicts various emotions such as hope or fear (Ellsworth & Smith, 1988; C. A. Smith & Ellsworth, 1985).

The elicitation of emotions such as fear or anxiety is quite common among clinical anxiety disorders especially in the face of uncertainty (Boswell et al., 2013; Carleton, 2016b). Uncertainty is a hallmark of various anxiety disorders such as generalized anxiety disorder, obsessive-compulsive disorder, and social anxiety disorder (Carleton, 2016a). A fear of the unknown and intolerance of uncertainty is common among those diagnosed with anxiety disorders. In this context, unknown or uncertainty is defined as the perceived absence of key, salient, or relevant information at any level of consciousness (Carleton, 2016b). Importantly, individuals with high anxiety tend to have cognitive biases where they overvalue negative information more than positive information especially when information is ambiguous. Ambiguity is defined as resulting from features perceived as equivocal or when there isn't enough information to interpret a situation in one way (Carleton, 2016b). However, individuals

high in anxiety are more likely to interpret ambiguous information as threatening even if that information could be interpreted neutrally (Hertel & Mathews, 2011; Manuel & Castillo, 1997).

Another form of ambiguity or uncertainty is attitude ambivalence where one has a conflicted view or attitude. Attitude ambivalence was initially defined by Scott (1966) as the degree to which an attitude has both desirable and undesirable components. Generally, attitude ambivalence occurs when one has two different attitude components comprised of positive and negative valence with similar intensity (Thompson et al., 1995).

Thus far, I examined the various definitions of uncertainty across various subfields. Each definition has common features that can be used to derive a shared definition of uncertainty. One feature common among all definitions of uncertainty is this idea of a lack of information, whether it sources from the self or the environment. Another commonality among these definitions is unknown probabilities or being unable to predict what will happen. Thus, a lack of information and an inability to predict what will happen are two key elements defining uncertainty.

How do people respond to this lack of information or inability to predict what will happen? How one engages with uncertainty will depend on how one appraises it and whether they find uncertainty to be threatening.

From Definition to Understanding How People Engage with Uncertainty in Daily Life

From an evolutionary perspective, uncertainty may be aversive (Hirsh et al., 2012; Hogg, 2000). Not knowing where the predators are or where the next food source will come from is threatening to one's survival. Thus, aversion to uncertainty could have been critical to our survival (Carleton, 2016b, 2016a; Hirsh et al., 2012). The generalized unsafety theory of stress (GUTS) provides an evolutionary account for why humans perceive uncertainty as aversive

suggesting that our default stress response is always on and only when safety is perceived, the stress response turns off. In the presence of uncertainty, an absence of safety is generally perceived, causing the stress response to stay on (Brosschot et al., 2016). This strategy has an evolutionary advantage as it allows people to be ready to either fight or flight in times of danger. In response to this aversion to uncertainty, humans are motivated to reduce it and keep it at a manageable level (Hirsh et al., 2012). But, in a world where people are no longer being chased by bears or unsure of where our next meal will come from (at least most people), is avoiding uncertainty always adaptive?

I start with examining some ways in which one may avoid uncertainty. Skeptical philosophers discussed navigating uncertainty using probability to assign a specific likelihood to each outcome or alternative to reduce the uncertainty (Annas & Barnes, 2000; Kozyreva et al., 2019). The problem with this idea is that one does not always know the probabilities of every outcome or even every possible outcome. Even if every possible outcome is known, it may be impossible to assign probabilities to it (Kozyreva et al., 2019; Kozyreva & Hertwig, 2021). For example, consider a situation where one is diagnosed with a chronic and rare disease for which there aren't many treatment options. One may feel uncertain about their life going forward in terms of what it is going to look like, how this disease will impact their career and relationships, and its effects on their mental health. One cannot assign probabilities to the various outcomes on their mental health or how it may impact their relationships or career.

Further, most people do not put in the cognitive effort to reduce uncertainty by calculating probabilities. Bounded rationality suggests that humans have cognitive limitations that reduce the effort they put in when making decisions (Simon, 1990). Rather people use heuristics or quick rules of thumb to navigate a situation. The constraints posed by human

cognitive architecture only allow a fraction of potential outcomes to enter one's perception. Additionally, other factors such as how information is presented in the environment and how one interprets information all affect how one makes decisions under uncertainty. Thus, one often uses strategies or heuristics that are appropriate to the environment to navigate uncertainty, thus adapting to the environment (Kozyreva et al., 2019; Kozyreva & Hertwig, 2021).

The theory of uncertainty management provides a similar explanation of how people engage with uncertainty, suggesting that people adapt in the face of uncertainty. Brashers and colleagues (2009) suggest management of uncertainty depends on how one perceives it: whether it is harmful or beneficial to one. Depending on how uncertainty is appraised, one chooses how they respond to it and whether they avoid it or embrace it. If uncertainty is perceived as harmful, it leads to subsequent emotions like fear, anxiety, worry, and stress. If the uncertainty is perceived as beneficial, it may lead to emotions such as hope or optimism. The responses and strategies used to manage uncertainty will change depending on whether it is perceived as beneficial or harmful (Brashers et al., 2000).

One's response to managing uncertainty can be explained by the extended process model of emotion regulation which proposes a framework for how we regulate emotions (Gross, 2015). Based on this model, one first experiences or notices something in the real world (e.g., getting laid off from work), and perceives that situation (e.g., this is an uncertain situation), and then assigns a valuation to it either as beneficial, harmful, or indifferent to oneself (e.g., getting laid off work is harmful to me). Essentially, the valuation stage examines the difference between the perceived world and the desired (goal/target) world (Gross, 2015). The last stage is action where one takes action based on the valuation stage to address the gap between the perceived and desired world (e.g., experiencing fear, shame, and negative emotions). Valuation systems can

interact such that a second level valuation system can exist where the output of the first valuation system becomes the input to the second valuation system. The negative emotions experienced from getting laid off work is the output of the first valuation system and input of the second valuation system. The negative emotions (e.g., fear, shame) become the world which may be perceived negatively and as harmful to oneself thus one might engage in emotion regulation strategies to down-regulate those negative emotions (Gross, 2015).

When uncertainty is perceived as harmful, one may engage in behaviours such as information seeking to reduce uncertainty and down regulate negative emotions. For example, when patients with chronic illnesses such as HIV or AIDS appraised uncertainty as dangerous, they experienced negative emotions like anxiety and fear and in response, sought information on how to cope with this disease or information to alleviate certain symptoms (Brashers et al., 2000). Thus, in situations where uncertainty is perceived as harmful, avoiding or reducing it via emotion regulation strategies involving situation selection (e.g., avoiding situations which may be perceived as uncertain) may be perceived as adaptive, at least in the short-term.

When uncertainty is perceived as beneficial, one may engage in behaviours to escalate or maintain the uncertainty. For example, if one perceives that knowing the survival chances or prognosis of a disease is distressing, then one may actively avoid that information as a strategy to maintain or escalate uncertainty because certainty is perceived as threatening. Similarly, one may not want to be tested for HIV fearing that the results might be positive. In this case, avoiding information sustains the uncertainty since seeking information can be threatening (Brashers et al., 2000).

Other situations in which one may want to maintain or increase the uncertainty is when they want to increase the positive feelings they are already feeling. For example, one study

demonstrates that in situations where positive emotions are evoked, uncertainty enhances the positive feelings even more so. In such situations, individuals want to preserve the uncertainty (Bar-Anan et al., 2009; Morriss et al., 2022). A practical example is when individuals are watching a suspenseful show, a thriller, or live TV—individuals want to maintain the uncertainty because it piques their interest. Uncertainty could also be effective for learning as it helps maintain one's attention to the source of uncertainty (Alquist & Baumeister, 2024); thus, asking questions and inducing uncertainty may be helpful for learning. Uncertainty may also be perceived positively when it is perceived as novel and challenging. One's interest or curiosity may be a motivating factor in wanting to know information and curiosity is associated with positive emotions like interest, surprise, and awe (Kashdan & Silvia, 2009). So, maintaining uncertainty may be perceived positively because it induces curiosity and positive emotions. Thus, in some situations, embracing uncertainty may be more adaptive than avoiding but how one engages with uncertainty depends on how it is appraised.

How is Uncertainty Appraised?

Luhmann and colleagues (2021) have identified a total of nine appraisals (i.e., valence, impact, predictability, challenge, emotional significance, change in world views, social status changes, external control, and uncommon) that can be used to describe or appraise an external event. The uncertainty management theory suggests that uncertainty can be perceived as beneficial or harmful but uncertainty can be appraised in other ways. One study demonstrates the association between daily uncertainty and negative affect suggesting that those who experienced uncertainty on a daily basis also experienced greater negative affect demonstrating that they appraised uncertainty as negative (Morse et al., 2024). Another study examined the daily uncertainty experienced by people living with multiple sclerosis. The authors found that the lived

experience of uncertainty was associated with a lack of control especially over one's body. Thus, uncertainty is also perceived as having a lack of control (Nissen et al., 2022). Previous literature has demonstrated that daily uncertainty is associated with negative affect and a lack of control, but no study has demonstrated the association between uncertainty in daily life and the other event dimension appraisals. In my thesis, I aim to directly examine whether uncertainty experienced in daily life is associated with these nine event dimension appraisals.

Typically, uncertainty is associated with negative life events such as loss of a job or living with disease (Brashers et al., 2000; Nissen et al., 2022). Other times, uncertainty may be associated with positive events like learning something new or watching a suspense thriller (Alquist & Baumeister, 2024; Kashdan & Silvia, 2009). In this thesis, I want to examine when or for which life events uncertainty is perceived the most — positive, negative or neutral.

Additionally, there is some research examining sex and age differences in experiencing uncertainty. One study suggests that women tend to experience more ambiguity than men, yet another study demonstrates that women tend to be more adaptive than men when responding to uncertainty (Borghans et al., 2009; Washburn et al., 2005). There is also some evidence suggesting that older adults tend to be less averse to ambiguity compared to younger adults (Sproten et al., 2010). In this thesis, I examined who experiences uncertainty more in terms of sex and age.

How Does One Decide Which Strategy to Engage in When Navigating Uncertainty?

Having identified an event as uncertain, individuals may engage in various cognitive or motivational strategies such as information seeking, avoidance of information, approaching the challenge and so on to manage uncertainty. One may also aim to downregulate negative affect or upregulate positive affect (Gross, 2015). Knowing when to use which strategy when feeling uncertain requires engaging in metacognitive processes (Grossmann & Johnson, 2025). Broadly, metacognition is the ability to monitor, understand, and regulate one's cognitive processes (Flavell, 1979). Perspectival metacognition is a process which allows one to easily shift their attention between multiple propositions or alternatives creating deeper insight into the issue or interest which allows one to see divergent perspectives (Grossmann et al., 2020). Intellectual humility involves the process of perspectival metacognition because one has to shift their attention between their opinions and those of others to consider that others may be right and they may be wrong. Other features involving perspectival metacognition include perspective-taking or recognizing others' viewpoints, considering how a situation may change or unfold (recognition of change), and searching for a compromise especially in situations of conflict (Brienza et al., 2018; Grossmann et al., 2020).

While people may engage in various metacognitive strategies when uncertain, it is unclear when they engage in metacognitive processing especially perspectival metacognition and which strategies they engage in. In essence, in my thesis I aim to find the key appraisals and metacognitive reasoning associated with uncertainty.

Measurement of Uncertainty

Common measures of uncertainty rely on self-reports of general dispositions (i.e., trait-based measures) such as the intolerance of uncertainty scale (Carleton, 2012) or event-specific responses to questions like "how much uncertainty did you experience during this choice" (Morse et al., 2024). Notably, these self-report measures are subject to various biases. For instance, one may not be aware of how one feels unless one is asked about it. One may also not recall the emotions one experiences accurately, relying on general cultural scripts, instead (Kahneman et al., 2004; Schwarz et al., 2009). An alternative to such questionnaire-based measures involves unstructured open-ended responses, in which one simply describes experiences for target events, with coders typically annotating types of affective reactions people spontaneously provide in such unstructured reports. However, annotation can be costly, time-intensive, difficult to establish inter-rater reliability, and for larger sample sizes simply not feasible. Fortunately, recent advances in natural language processing (NLP) suggest that one can overcome the latter challenges by relying on automated AI-driven systems for annotating unstructured text responses on a wide range of psychological constructs (e.g., emotions like happiness or sadness; Ratje et al., 2024; intellectual humility, Stavropoulos et al., 2024; open-minded cognition, Elnakouri et al., 2024). Below, I will describe some of these advances, and elaborate on the specific steps through which NLP can afford advances for measuring uncertainty.

Why natural language processing?

Natural language processing is a field at the intersection of computer science, artificial intelligence, and linguistics which uses algorithms and models to help computers process, understand, and generate human language. NLP methods can be as simple as counting word

frequencies to more advanced methods such as using large language models (LLMs) to generate text. There are many applications of NLP in behavioural sciences such as conducting exploratory content analysis to get an understanding of the data or analyzing text data to identify a psychological construct (Feuerriegel et al., 2025).

NLP includes various methods and techniques but before analyzing text data, it has to be prepared. This preparation of text data is known as text pre-processing and is often the first step in the NLP pipeline. This step involves cleaning the text data and may involve various steps such as removing stop words (e.g., a, the, you) or making all words lowercase. The next step is text representation where text is converted into vectors in a multidimensional space so it can be used by various models and methods for further processing. The word embeddings or paragraph vector model takes semantics or meaning of words into account such that words that are closer in meaning are placed closer in the multidimensional vector space. This text representation acts as an input to various modelling methods that then delivers the output. For example, Large Language Models (LLMs)—i.e., machine learning models such as ChatGPT which are pretrained on large and diverse datasets—use these text representations to produce output. LLMs can produce an output such as binary classification of text data by using zero-shot prompting, few-shot prompting, or fine-tuning. In zero-shot prompting, the LLM responds to the prompt without additional input or training whereas in few-shot prompting, LLMs are provided with additional information and examples. Finally, in fine-tuning, the LLM is provided with a large set of labelled data to improve performance on a specific task (Feuerriegel et al., 2025).

Recent scholarship built on these advances to evaluate viability of using LLM-based classification of psychological content (e.g., Rathje et al., 2024; Stavropoulos et al., 2024). For instance, Stavropoulos and colleagues (2024) developed a pipeline relying on zero-shot and few-

shot prompting to classify presence of social cognitive and metacognitive characteristics—intellectual humility, open-mindedness to how events may unfold, perspective-taking, and search for compromise—in a dataset of 347 unstructured and typed reflections. Human coding or classification was used as the comparison benchmark against OpenAI's commercial GPT-3.5 and GPT-4 models and an open-source model (RoBERTa). For few-shot prompting, the authors used existing definitions from the human coding guide and iteratively refined them using GPT-4. Similarly, they used examples from the human coding guide and refined them using GPT-4 instructing it to give additional examples of text when the feature is absent and present and provide a justification for it. For zero-shot prompting, they only used the standard definition of each social/metacognitive characteristic. Using the definition and examples, the authors instructed the models to produce a verbal binary output of the unstructured text (i.e., whether the metacognitive feature is present or absent) and generate a justification for it. Across all four metacognitive features, 19 out of the 25 LLM-based classifiers had over 80% agreement with human coders and the F1 scores were above 0.85. Additionally, the few-shot trained models performed well showing higher agreement with human coders compared to zero-shot. Thus, there is evidence that emerging AI systems are able to accurately classify metacognitive features of wise reasoning (Stavropoulos et al., 2024).

I build on these advances in automated text classification, because this approach can take large quantities of data and generate output in a short amount of time. Further, for data with thousands of unstructured text responses, human coding can be costly, unreliable, or simply not feasible. For this thesis, I adopted the Stavropoulos et al. (2024) method to evaluate a range of commercial and open-source models for classification of uncertainty in reflections on daily life events. The open-ended text responses came from a large dataset from the Pathways to Wisdom

project (Dorfman et al., 2022; J. A. Smith et al., 2025) which is a longitudinal, daily diary study where participants responded to the most meaningful event of their day. Since there are multiple entries per person, I was able to capture both trait and state uncertainty.

Trait and State Uncertainty

Traits are how one typically behaves or one's average response while states are one's response or behaviour at a given point of time in a specific context. According to whole trait theory, traits are simply density distributions of states (Fleeson & Jayawickreme, 2015). If one's distribution of how much they stress in daily life is put together, it represents their trait of neuroticism. Typically in previous studies, uncertainty or intolerance of uncertainty has been measured as a trait, but some studies have also examined uncertainty as a state using ecological momentary assessments (Morse et al., 2024). Trait uncertainty captures one's disposition to being uncertain while state uncertainty captures whether one is uncertain or not in the moment. It is important to capture both state and trait uncertainty because their relationship may differ with other variables such as affect and perception. Additionally, measuring both trait and state uncertainty gives information about the mechanism of how that variable develops or its underlying process (Fleeson & Jayawickreme, 2015). For example, greater state uncertainty was associated with greater daily negative affect which contributed to greater intolerance of uncertainty at the trait level (Morse et al., 2024). Thus, studying both trait and state uncertainty can allow to explain the various relationships between the research variables at different levels. Studying both trait and state uncertainty may also shed light on the social-cognitive mechanism underlying the relationship between the variables (Fleeson & Jayawickreme, 2015).

The Present Study

In my thesis, I first sought to evaluate automated approaches for classifying open-ended text responses as uncertain and not uncertain. Upon identifying the most robust automated system, I used it to understand individual and situational differences in perceptions and expression of reported uncertainty in one's daily life. I examined demographics and who is more likely to experience uncertainty in terms of sex and age. Next, I examined emotional and appraisal profiles of uncertain events in people's lives. I also examined for which types of situations people perceive life events as uncertain. Finally, I addressed how people reason about uncertain events, with a particular focus on wisdom-related perspectival metacognition. Throughout my thesis, I probed effects on the trait- and state-levels of analyses.

CHAPTER TWO: Methods

This study received ethics clearance by the University of Waterloo Research Ethics Committee (ORE # 23053). I performed a secondary data analysis of the Pathways to Wisdom project. Please refer to the original sources for full recruitment and data collection details (Dorfman et al., 2022; J. A. Smith et al., 2025). The Pathways to Wisdom project was preregistered however since this is an exploratory study, there are no preregistered hypotheses for my research questions.

Participants

Participants were recruited by placing ads on Facebook and through Amazon's Mechanical Turk (mTurk). Researchers recruited 461 participants from Canada and the U.S, and an additional sample of 127 U.S. participants to account for attrition in the later waves of the study since this was a one year long longitudinal study. For the first wave, I analyzed an initial sample of 499 participants, and the sample size decreased over time (see Table 1 for attrition rates). Researchers removed participants for reporting inconsistent age or gender across waves, and incomplete responses. The entire study was conducted online; thus, participants were sent an email link to complete the surveys conducted on Qualtrics.

The community sample was diverse in terms of demographics. The participant sample consisted of 69% female; $M_{age} = 37.89$; $SD_{age} = 12.95$; Age range = 18-82. The income ranged from $10,000 - $100,000 with the median ranging from $35,001 - $50,000. In terms of racial and ethnic self-identification, 78% identified as White, 6% as Black, 5% as Asian, 4% as South/South-east Asian, 4% as Latinx, and 2% as mixed race or other. In the sample, 90% were high school educated, 22% had a college education, 33% had a Bachelor's degree, and 24% had a professional or graduate degree.

Participants were compensated for their participation with an Amazon gift card worth up to $100 CAD for completing all four waves or a $75 gift card for completing three waves. To motivate retention after the first wave, the renumeration increased for follow-up waves (see Table 1 for payment details by wave). Participants received remuneration after all data collection was completed. Those who completed all four waves entered a raffle offering an additional $100 CAD.

Table 1

Participants, Attrition Rates, and Payment

Wave	Participants	Attrition (%)	Payment (CAD)
1	499		$20
2	282	43	$25
3	276	3	$25
4	186	17	$30

Procedure

This year-long longitudinal study consisted of four waves approximately 2.5 months apart and each wave lasted ten days. The first day of each wave is termed wave data where participants are asked to report on major adverse events in their life. The other nine days is termed daily data where participants reported on the most meaningful or significant event of their day. Demographics were collected on the first day of the first wave (i.e., sex, age, religion, education, ethnicity, political orientation, household income, and residential area). On subsequent first days of the other waves, only age and sex were collected. For the wave data, participants were asked to report an adverse event (e.g., health-related challenge, marital conflicts, economic setbacks) that they experienced in the last two months. They described the

situation using open-ended text responses and subsequently responded to various questionnaires like the Situated Wise Reasoning Scale, emotion items from PANAS, Event Dimension Scale and more. In this study, I only examine the daily data and no other parts of the larger project (J. A. Smith et al., 2025). Information about the wave data on adverse events is reported elsewhere (Dorfman et al., 2022).

For the daily data, participants recalled the most significant event of their day. First, participants checked off the type of event experienced that day (i.e., conflict, celebration, enjoyable social event, social rejection, annoying event, sad or bad news, and none of the above). If they experienced neither the positive nor negative event types, they checked off "none of the above" which is referred to as a meaningful event. Then participants reported about the event, who was involved, and when it occurred followed by three open-ended prompts (shown below) where participants described the event and their thoughts and feelings about it. Depending on the event type chosen, various questionnaires were presented to participants regarding the reported event. A complete workflow and description of all surveys and items is available on Open Science Framework (https://osf.io/vkrpu).

Open-ended Prompts. 1) "As you were thinking about this situation, what thoughts and feelings came to your mind? In the space provided, please write at least a few sentences to fully describe what you thought and felt." 2) "What are the specific things you did in response to today's event?" 3) "Anything else? Please use the space below to report any other ways you responded or planned to respond."

Event Dimension Scale. The event dimension scale was included in the workflow for all event types reported. The event dimension scale examines how one appraises or perceives an event (Luhmann et al., 2021). It consists of nine statements with varying dimensions such as

valence (i.e., negative), impact, predictability, challenge, emotional significance, change in world views, social status changes, external control, and extraordinariness (i.e., uncommon event). Participants rated all dimensions or statements on a 5-point scale (1 = *not at all,* 5 = *very much*).

Self-distancing. When reflecting on the event, all participants were asked to indicate the extent to which they took a distanced perspective on the self (Brienza et al., 2018). The self-distancing questionnaire consisted of four items (α = .92): 1) Wondered what I would think if I was somebody else watching the situation. 2) Tried to see the conflict from the point of view of an uninvolved person. 3) Asked myself what other people might think or feel if they were watching the conflict. 4) Thought about whether an outside person might have a different opinion from mine about the situation. Participants rated all items on a 5-point scale (1 = *not at all*, 5 = *very much*, 6 = *not applicable*). Given high reliability, I averaged responses across these four items to obtain the final self-distancing score.

State Specific Challenge and Threat. Participants reported to the extent to which they viewed the event as a challenge or a threat (D'Zurilla et al., 2002), providing responses for four items (e.g., "I was unsure of whether I could handle the situation", "When I faced this situation I felt threatened and afraid"). Participants rated all items on a 5-point scale (1 = *not at all*, 5 = *definitely*). For the purpose of this study, only the unsure and threat items were used for separate analyses.

Perspectival Metacognition. This questionnaire was only presented to participants who reported experiencing an annoying, rejection-related, or conflict type event. To assess specific metacognitive features, participants filled out relevant subset of items from the *S*ituated *Wi*se reasoning *S*cale (SWiS; Brienza et al., 2018). This measure captures four metacognitive features: 1) *intellectual humility* (4 items, e.g., "Double-checked whether my opinion on the situation

might be incorrect", α = .82); 2) *open-mindedness to change* (4 items, e.g., "Believed the situation could lead to a number of different outcomes", α = .82); 3) *perspective-taking* (4 items, e.g., "Considered the perspective of the other person(s) involved in the situation", α = .87); 4) *search for compromise* (5 items, e.g., "Though it may not have been possible, I searched for a solution that could result in most people being satisfied", α = .84). Participants rated all items on a 5-point scale (1 = *not at all,* 5 = *very much*, 6 = *not applicable*). Given high reliability, I averaged respective items to obtain final scores for each metacognitive feature.

Emotions. Participants reported on how they felt when the event was taking place. Emotion items were obtained from PANAS with a focus on selecting for a variation in valence and arousal. Thus, four positive emotions with low (i.e., happy and calm) and high (i.e., excited and joyful) arousal were selected along with negative valanced emotions also ranging from low (i.e., annoyed, sad, blue) to high arousal (i.e., angry, anxious, afraid; Watson et al., 1988). Participants rated each emotion on a 6-point scale (1 = *not at all,* 6 = *very much*). Emotional ambivalence was calculated using emotion ratings and Griffin's formula (Equation 1). An average of positive emotions represented by *P* in Equation 1 and an average of the negative emotions represented by *N* were taken for each participant. This formula accounts for both the intensity and direction of ambivalence (Thompson et al., 1995).

$$\frac{P+N}{2} - |P - N| \qquad (1)$$

Natural Language Processing and AI Coder

Using participants' open-ended text responses on their thoughts and feelings about the most significant event of their day, I classified them as uncertain and not uncertain using a similar pipeline to the one described by Stavropoulos and colleagues (2024). To simplify the pipeline and code, the authors constructed a machine-readable coding guide in JSON format. The

AI Coder (https://futurescape.uwaterloo.ca/ai-coder/) is the shell or webpage with the underlying pipeline used to streamline the process of identifying complex psychological phenomenon (Stavropoulos et al., 2024). It uses OpenAI's commercial large language models such as GPT-4o-mini and GPT-4o for feature identification (presence and absence) in text. The webpage requires OpenAI API key, the csv file with the text to be classified, the name of the phenomenon (i.e., uncertainty), its definition, and three examples of sentences where the feature (i.e., uncertainty) was present and three examples where it was absent. The definition of uncertainty is derived from the literature review from judgment and decision-making (Kahneman & Tversky, 1982; Ülkümen et al., 2016), cognitive-emotion theories (Ellsworth & Smith, 1988; C. A. Smith & Ellsworth, 1985), and clinical literature on fear of the unknown (Carleton, 2016b). I examined the definition of uncertainty provided in these sources to identify similar elements to obtain a shared definition. The chart showing common elements is provided in Appendix A, Table A1. I used the following definition: "Uncertainty is an expression of not knowing or understanding information accompanied by an expression of being unable to predict what will happen in the future." Most examples were chosen from the text responses that participants wrote, but some were developed iteratively by prompting GPT-4. The examples were carefully selected to represent uncertainty that could be present in various forms (i.e., through emotions such as worried and anxious, phrases like "I'm not sure", or genuine questions). The absent feature examples were also selected to reflect clear examples where uncertainty is not present such as in stating factual statements of what they did that day, but also subtle examples like rhetorical questions where the model may make a mistake of classifying it as uncertain. The examples are provided in Appendix A, Table A2.

I first cleaned the text file with the open-ended responses in *R* removing meaningless responses such as those with blank entries or words like “N/A” or “none”. I also filtered out responses with less than seven words as they were meaningless and made all the letters lowercase. I then added all the information to the AI Coder including the definition and examples, and the file with the text. The output of this classification of text was a csv file with multiple columns next to the statement stating whether uncertainty was present or absent with justifications (example shown in Appendix A, Figure A1). The combination of the techniques and models resulted in four columns of classification data (i.e., few-shot GPT-mini, few-shot GPT, zero-shot GPT-mini, zero-shot GPT). In addition to the two commercial models, I also used an open-source model (BART-large-MNLI)—with the zero-shot classification technique only—from the Hugging Face library (https://huggingface.co/facebook/bart-large-mnli). I used *R* for zero-shot classification using the BART-large-MNLI open-source model where I asked it to classify each statement as uncertain, certain or neutral, as these labels improved the accuracy of classification of text compared to uncertain (present) or not uncertain (absent). Each text response was assigned three percentage scores indicating the degree to which it expressed uncertainty, certainty and neutrality. All three percentage scores added to 100%. I used the open-source model to compare with the commercial models and examined which model performs better. When comparing with commercial models, I classified a statement as 'uncertain' (coded as 1) if its uncertain label score exceeded 0.90. Statements with uncertainty scores below 0.90 were labeled as 'not uncertain' (coded as 0). This 0.90 threshold was chosen after manually reviewing several hundred examples, which showed that statements scoring below 0.90 were typically not uncertain.

To evaluate model classification accuracy, I compared a subsample of responses ($k = 100$) against the classification scores provided by three human coders, who received the same instructions as the pipeline provided in the OpenAI models for classification. Any discrepancies between the coding of humans were solved and a new column was created where all human coders agreed on one answer (i.e., whether the statement was uncertain or not uncertain). Thus, each model was compared to one unanimous column agreed upon by human coders (used as ground truth rating).

Data Analysis

I analyzed all data using *R* statistical software (v4.3.1; R Core Team, 2023) and specifically the following packages: *lme4* (Bates et al., 2015), *dplyr* (Wickham et al., 2014), *emmeans* (Lenth, 2017), *tidyverse* (Wickham et al., 2019), *ggplot2* (Wickham et al., 2007), *text* (Kjell et al., 2023), and *sjPlot* (Lüdecke, 2013). To analyze data, I used linear mixed models with participants as a nested factor considering the repeated entries for each participant. I used mixed models to account for the variation in the dependent variable by individual participants entries, with event type (uncertain vs. not uncertain) as a categorical predictor.

CHAPTER THREE: Results

Reliability and Validity of AI Coder

Reliability of AI Coder

First, I checked whether the AI coder and the opensource model that classified open-ended text responses as uncertain and not uncertain were reliable and valid. To assess reliability, I examined the intra-class correlations (ICC) and Cohen's κ between each of the commercial and opensource models and human coders. Cohen's κ is typically used when the data is categorical which is the case here since uncertainty is a categorical variable coded as 0 and 1 (not uncertain versus uncertain). ICC is also an appropriate choice to assess reliability because ICCs can be used for discrete data and since uncertainty was coded as 0 and 1, this qualifies as discrete data (Ten Hove et al., 2024). The parameters for an ICC were a two-way design, type was consistency, and unit was average. Since the raters' ratings were averaged, the unit was average and type was consistency because I only needed the raters' ratings to correlate positively, not be an exact match (Ten Hove et al., 2024).

To assess accuracy of each of the models, I also examined F1 scores. F1 scores represent the precision of the model taking the ratio of true positives over a sum of true positives and false positives (Equation 2). True positives occur when both human coders and the classifier identify a statement as uncertain; true negatives occur when both label it as not uncertain. False positives arise when the classifier incorrectly labels a not uncertain statement as uncertain causing it to overgeneralize, while false negatives occur when it fails to identify an uncertain statement causing it to miss. Sensitivity is another metric that captures the proportion of positives in the set of statements that are correctly identified and is the proportion of true positives over the sum of true positives and false negatives (Equation 3). Specificity is a metric that captures the proportion of negatives in the set of statements that are properly identified and is the proportion

of true negatives over the sum of true negatives and false positives (Equation 4). Table 2 shows all reliability estimates and metrics by the combination of model and technique type. Although the opensource model had a perfect sensitivity score and did not overgeneralize, the specificity score was the lowest meaning that it missed a lot of statements classified as uncertain. While the specificity score for the zero-shot GPT model was the highest meaning it's not missing any uncertain statements, the sensitivity score is low meaning it overgeneralizes. Based on the reliability estimates and accuracy, the few-shot GPT commercial model was the most reliable and accurate. The sensitivity and specificity scores were also balanced compared to other models. Thus, I used the results from the few-shot GPT model for all subsequent analyses.

$$Accuracy = \frac{True\ positives}{True\ positives + False\ positives} \quad (2)$$

$$Sensitivity = \frac{True\ positives}{True\ positives + False\ negatives} \quad (3)$$

$$Specificity = \frac{True\ negatives}{True\ negatives + False\ positives} \quad (4)$$

Table 2

Reliability Estimates by Combination of Model and Technique, with Human Coders as Criterion

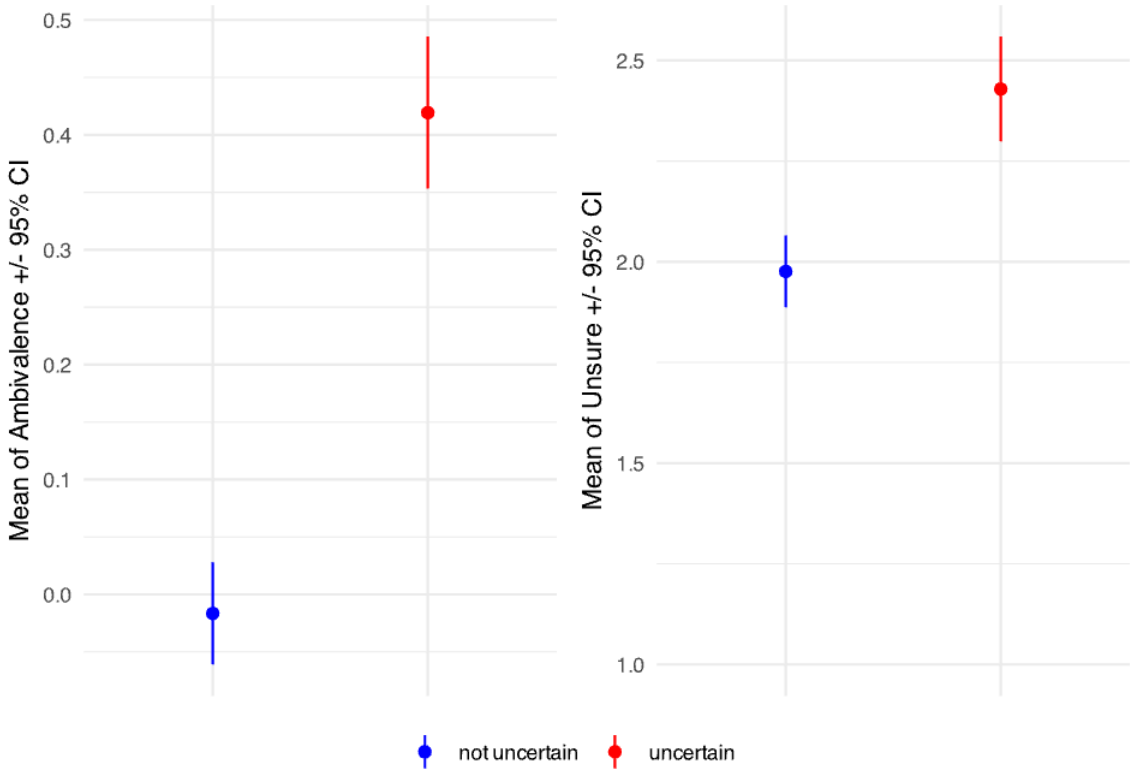
Reliability metric	Fewshot GPT 4o	Fewshot GPT 4o-mini	Zeroshot GPT 4o	Zeroshot GPT 4o-mini	Zeroshot opensource
ICC	.83	.81	.76	.80	.79
Cohen's κ	.71	.67	.61	.64	.60
*F*1	.87	.85	.84	.83	.80
Sensitivity	.87	.90	.70	.93	1.00
Specificity	.87	.83	.90	.79	.71

Criterion Validity

To assess criterion validity of the few-shot GPT model, I examined whether uncertainty coding predicts emotional ambivalence and another item of being unsure from the State Challenge and Threat questionnaire (e.g., "I was unsure of whether I could handle the situation."). Statements for which participants reported greater emotional ambivalence were more likely to be classified as uncertain, $b = 0.44$, $SE = 0.03$, $p < 0.001$. When participants reported being more unsure, those statements were also more likely to be classified as uncertain, $b = 0.45$, $SE = 0.06$, $p < 0.001$. Figure 1 shows the means of uncertainty for both emotional ambivalence and being unsure.

Figure 1

Means of Emotional Ambivalence and Being Unsure by Uncertainty



Demographics: Who is Likely to be Uncertain?

Participants reported whether they were male, female, or non-binary. There were 161 males, 357 females, and 2 non-binary. Since the non-binary sample was less than 1% and there was a greater proportion of females in the dataset, the final analyses examined whether females, or males and non-binary combined experienced greater uncertainty. Uncertainty was treated as a binary variable with 0 representing statements coded as not uncertain and 1 representing statements coded as uncertain. Using a generalized linear mixed model with uncertainty as the dependent variable, sex as a fixed effect predictor, responses nested in participants (random intercept model), and males as a dummy coded variable, I found that there was a greater proportion of statements coded as uncertain for females (M = .09, 95% CI = [.08, .11]) compared to males (M = .06, 95% CI = [04, .07]), b = 0.49, SE = 0.14, p = .001. Thus, statements reported by females were more likely to be classified as uncertain compared to those reported by males. Similarly, using a generalized linear mixed model with uncertainty as the dependent variable, age centered (age range: 18-82), and age centered squared as fixed effect predictors and responses nested in participants (random intercept model), I found no significant effect of age.

Uncertainty and Emotions

To examine the effect of uncertainty on emotions, I used a linear mixed model with emotion ratings as the dependent variable, emotion type, uncertainty, and their interaction term as fixed effects predictors, and responses nested in participants. Rather than taking the composite of negative and positive emotions, I analyzed each emotion separately to identify the specific emotions associated with uncertainty rather than simply focusing on valence. There was a main effect of type of emotion, $F(9, 94444) = 3404.97$, $p < .001$, a main effect of uncertainty, $F(1, 93143) = 10.59$, $p = .001$, and an interaction effect, $F(9, 94443) = 556.83$, $p < .001$. After following up with pairwise post-hoc comparisons using Tukey method correction for multiple

testing, I found that uncertain events were associated with higher ratings of being afraid, angry, annoyed, anxious, blue, and sad compared to not uncertain events. Also, uncertain events were associated with lower ratings of calm, excited, happy, and joy compared to not uncertain events. The descriptive statistics and simple effects are shown in Table 3, and a visual representation is displayed in Figure 2.

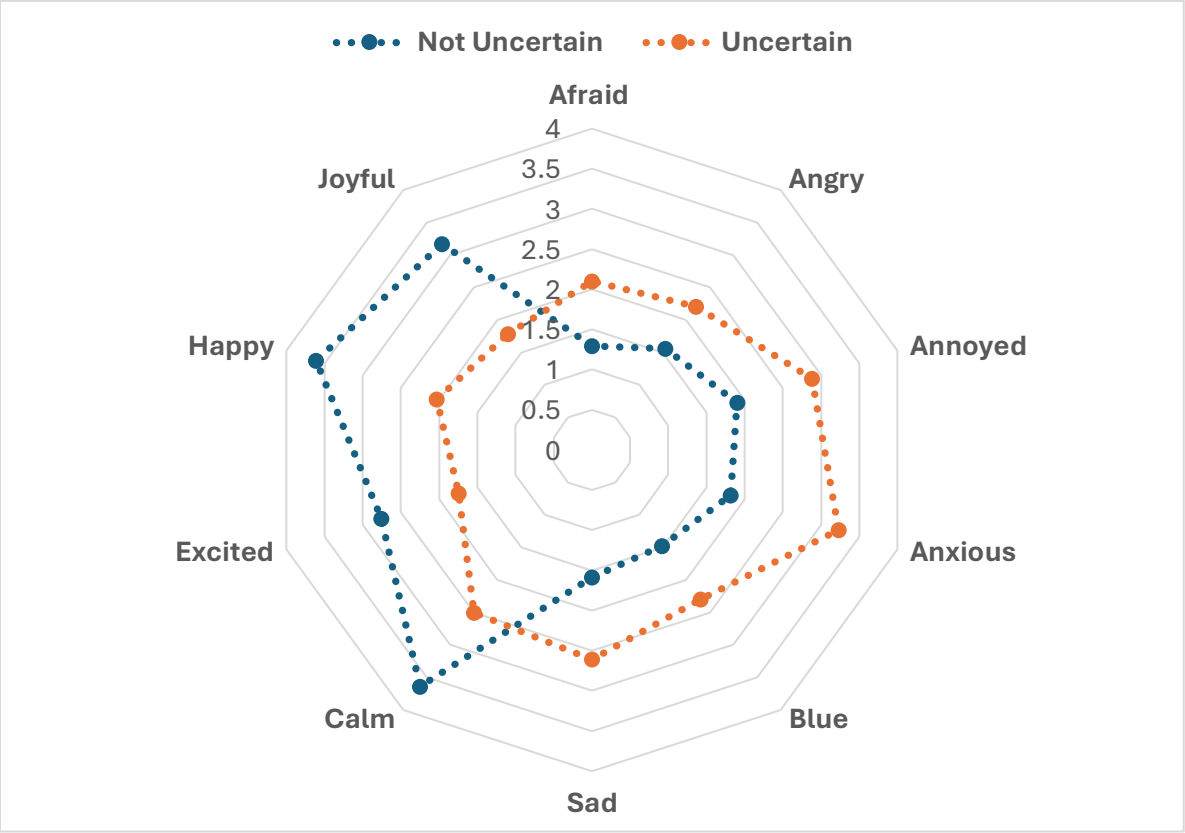
Table 3

Descriptive Statistics and Simple Effects of Uncertainty on Negative and Positive Emotions

	Not Uncertain *M* (*SE*)	Uncertain *M* (*SE*)	|*z*|	*p*-value
Afraid	1.29 (0.02)	2.10 (0.05)	16.15	< .001
Angry	1.56 (0.02)	2.20 (0.05)	12.80	< .001
Annoyed	1.90 (0.02)	2.88 (0.05)	19.45	< .001
Anxious	1.82 (0.02)	3.23 (0.05)	28.16	< .001
Blue	1.48 (0.02)	2.30 (0.05)	16.38	< .001
Sad	1.59 (0.02)	2.61 (0.05)	20.15	< .001
Calm	3.64 (0.02)	2.50 (0.05)	22.73	< .001
Excited	2.76 (0.02)	1.74 (0.05)	20.17	< .001
Happy	3.61 (0.02)	2.03 (0.05)	31.51	< .001
Joy	3.17 (0.02)	1.78 (0.05)	27.83	< .001

Figure 2

Mean Negative and Positive Emotion Ratings for Uncertain Versus not Uncertain Statements



How do People Perceive Uncertainty?

To examine how participants perceive uncertain events, I examined how participants appraised events classified as uncertain and not uncertain. To this end, I examined the ratings of each event along various event appraisal dimensions. I used a linear mixed model with appraisal ratings as a dependent variable, uncertainty (uncertain or not uncertain), event appraisal dimension, and their interaction as fixed effect predictors, event types (e.g., conflict, rejection, enjoying) as a fixed effect covariate, and responses nested in participants (random intercept model). Event type was included in the analysis as a covariate because the variance in how people perceive uncertainty will come from the type of event one reports. To control for this

variance, event type was a covariate rather than a moderator. This will improve the precision of the fixed effect predictors on the dependent variable. I will first report omnibus effects, before following up with pairwise post-hoc comparisons with Tukey method correction for multiple testing.

I observed a significant main effect of uncertainty, $F(1, 83110) = 124.17$, $p < .001$, type of appraisal, $F(8, 82949) = 2529.18$, $p < .001$, and a significant uncertainty by appraisal interaction, $F(8, 82949) = 135.03$, $p < .001$. When unpacking the interaction term, I observed that participants perceived uncertain events as more challenging, negative, in the hands of other people, less emotionally significant, less predictable, and less likely to lead to changed world views compared to not uncertain events. There was no significant difference in perceived reputation suffering, impact, and commonality of the event. All statistics are displayed in Table 4, and a visual representation of the data is provided in Figure 3.

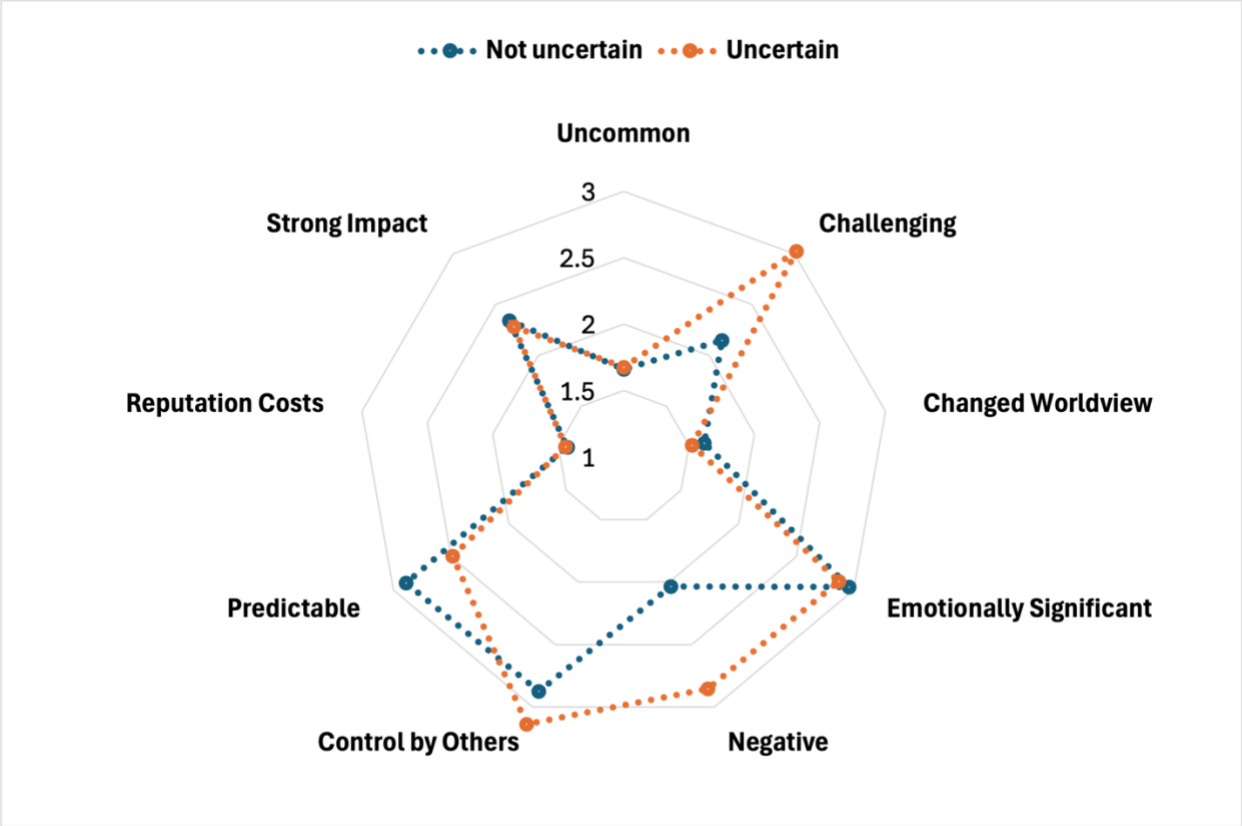
Table 4

Descriptive Statistics and Simple Effects of Uncertainty on Event Dimension Appraisals

	Not Uncertain *M* (*SE*)	Uncertain *M* (*SE*)	|*z*|	*p*-value
Challenging	2.15 (0.02)	3.02 (0.04)	23.34	< .001
Negative	2.03 (0.02)	2.86 (0.04)	21.89	< .001
Other control	2.87 (0.02)	3.14 (0.04)	7.04	< .001
Emotionally significant	2.96 (0.02)	2.87 (0.04)	2.28	.023
Predictable	2.89 (0.02)	2.49 (0.04)	10.76	< .001
Changed world views	1.62 (0.02)	1.52 (0.04)	2.45	.014
Reputation suffering	1.43 (0.02)	1.44 (0.04)	0.37	.714
Strong impact	2.34 (0.02)	2.28 (0.04)	1.51	.130
Uncommon	1.66 (0.02)	1.68 (0.04)	0.36	.716
Model Fit				
AIC	249694.25			
BIC	249936.89			
R^2 (fixed effects)	.244			
R^2 (total)	.302			

Figure 3

Mean Rating of Event Dimension Appraisals for Statements Coded as Uncertain Versus not Uncertain



Trait and State Effects of Uncertainty Appraisals

Next, I explored the typical or average tendency of a person to be uncertain, also known as trait uncertainty. I also explored state uncertainty by taking the deviation from each individual's average or typical tendency. I calculated trait uncertainty by grouping uncertainty scores across participants since we have multiple data points for a participant such that the trait uncertainty represents the proportion of statements coded as uncertain over all uncertain plus not uncertain statements for an individual. State uncertainty is calculated by taking the rating of an individual on a specific day and subtracting from their average or trait score.

In a linear mixed model, appraisal rating was the dependent variable, appraisal type, trait uncertainty, state uncertainty, and the interaction term between appraisal type and state and trait uncertainty were fixed effects predictors, event type was a covariate term, and responses were nested in participants. Participants who reported more uncertain events were more likely to perceive events as more challenging, negative, and in the hands of other people or other's control. Additionally, these people perceived the impact of the event to be less strong and less emotionally significant. At the same time, the more uncertain an event was relative to other events from the same person, the more challenging, negative, and in the hands of other people it was perceived to be. It was also perceived as less predictable and less likely to lead to changed world views. The model fit and Anova results are shown in Table 5. Figures 4 and 5 also display the change in appraisal ratings as a factor of trait and state uncertainty respectively.

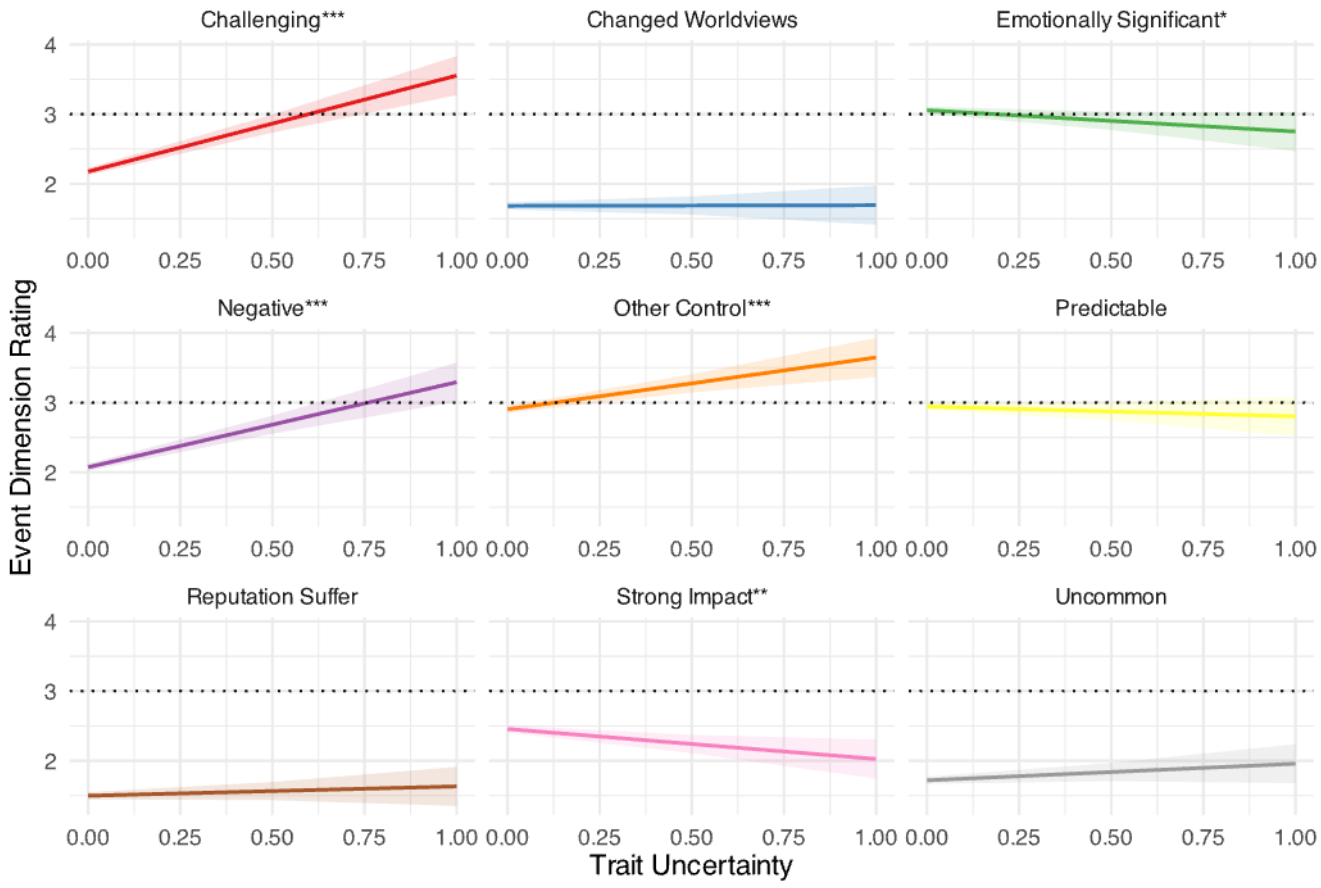
Table 5

Omnibus Anova Analyses and Model Fit for Trait and State Effects of Uncertainty on Appraisal Ratings

	F value	Numerator *df*	Denominator *df*	*p*-value
Trait uncertainty	6.81	1	539	.009
State Uncertainty	119.68	1	83028	<.001
Trait Uncertainty x Appraisal	38.56	8	82941	<.001
State Uncertainty x Appraisal	105.73	8	82941	<.001
Model Fit				
AIC	249655.82			
BIC	249982.46			
R^2 (fixed effects)	.246			
R^2 (total)	.303			

Figure 4

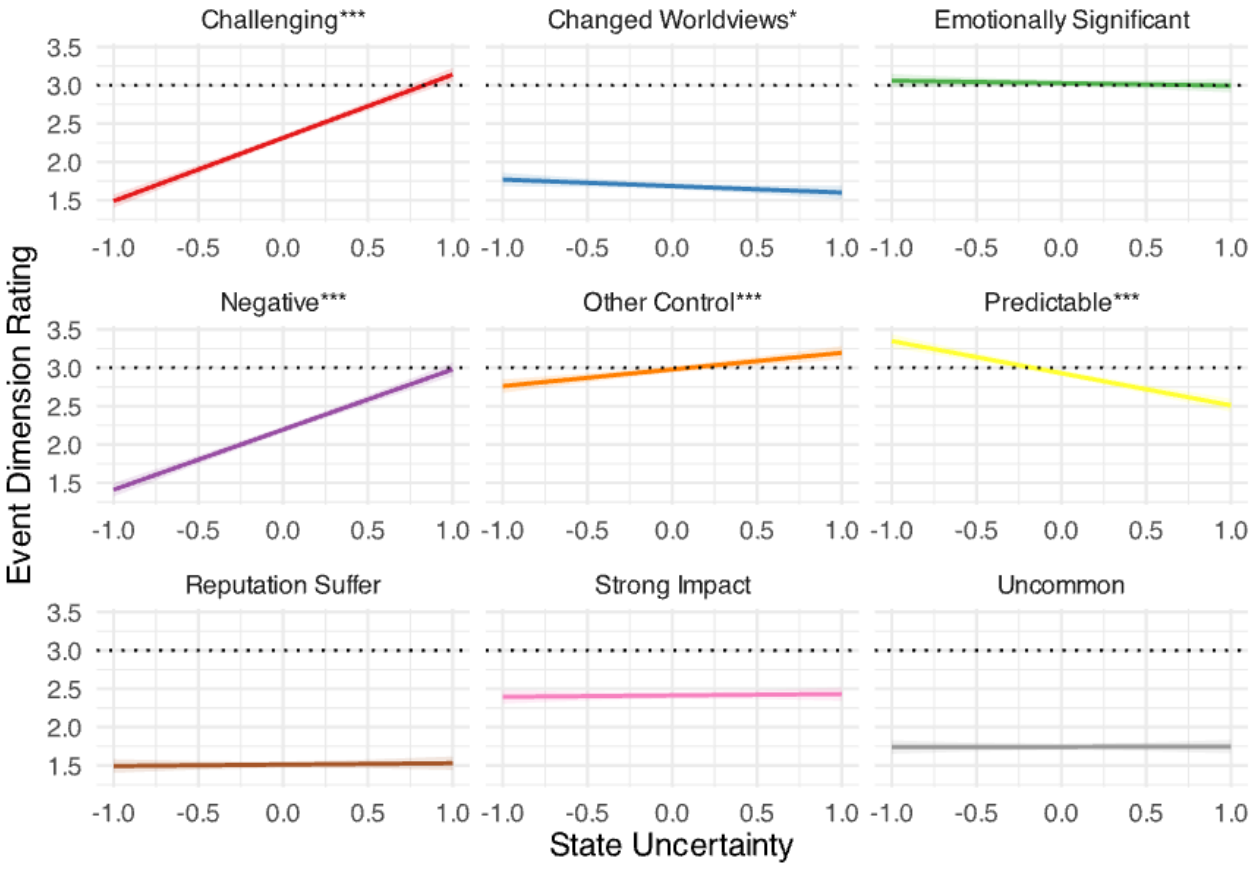
Simple Slopes of Trait Uncertainty on Appraisal Ratings



Note. Challenging: $b = 1.38$, $z = 8.80$; Changed Worldviews: $b = 0.01$, $z = 0.06$; Emotionally Significant: $b = -0.31$, $z = -1.96$; Negative: $b = 1.22$, $z = 7.80$; Other Control: $b = 0.74$, $z = 4.75$; Predictable: $b = -0.14$, $z = -0.90$; Reputation Suffer: $b = 0.13$, $z = 0.86$; Strong Impact: $b = -0.43$, $z = -2.75$; Uncommon: $b = 0.24$, $z = 1.52$. * $p < .05$, ** $p < .01$, *** $p < .001$. The dotted line represents the mid-point of the scale which ranges from 1-5.

Figure 5

Simple Slopes of State Uncertainty on Appraisal Ratings



Note. Challenging: b = 0.83, z = 20.74; Changed Worldviews: b = -0.08, z = -2.13; Emotionally Significant: b = -0.03, z = -0.80; Negative: b = 0.79, z = 19.74; Other Control: b = 0.22, z = 5.46; Predictable: b = -0.42, z = -10.54; Reputation Suffer: b = 0.02, z = 0.46; Strong Impact: b = 0.02, z = 0.47; Uncommon: b = 0.01, z = 0.08. * $p < .05$, ** $p < .01$, *** $p < .001$. The dotted line represents the mid-point of the scale which ranges from 1-5.

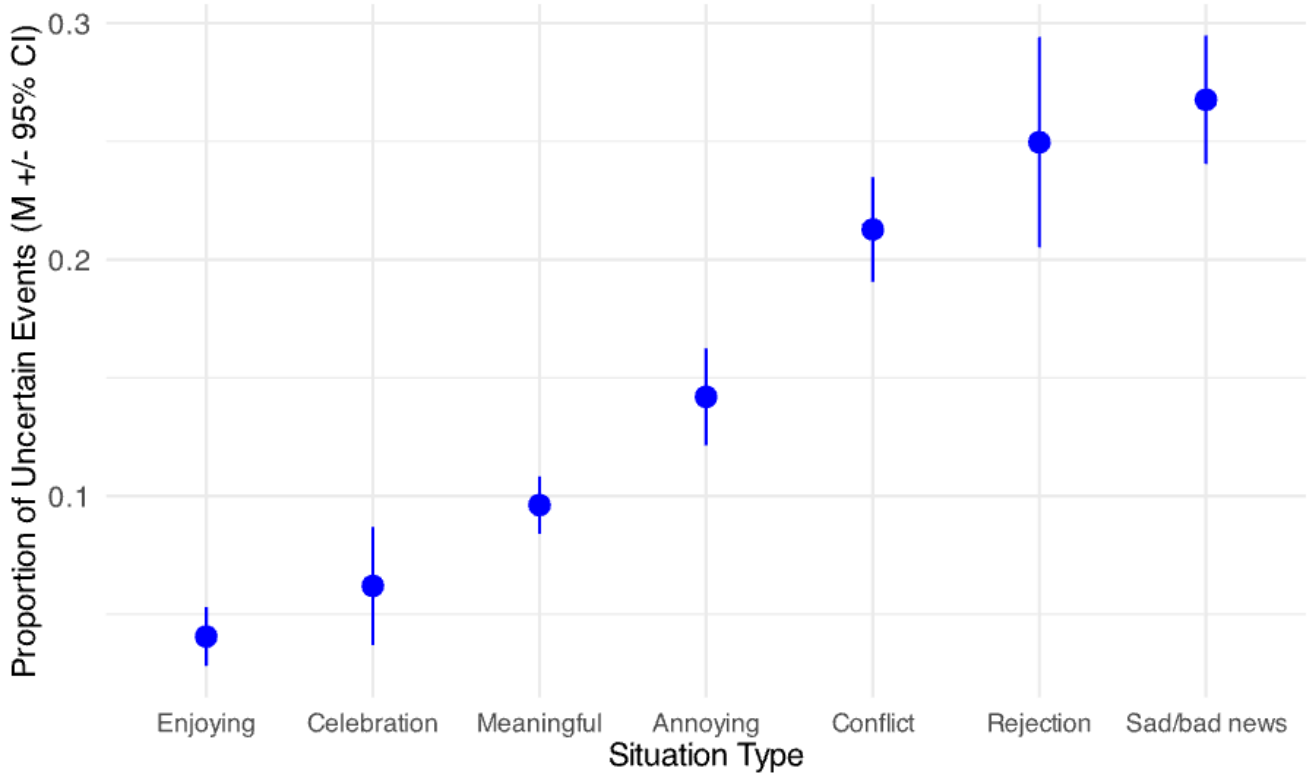
When are People More Uncertain?

Here I used a linear mixed model with uncertainty as the dependent variable and event type as the independent variable with participants as the random factor. All event types were

included in the same model. There was a main effect of event type, $F(6, 9493.4) = 78.63$, $p < .001$. After following up with pairwise post-hoc comparisons using Tukey method correction for multiple testing, I found that sad or bad news had the highest proportion of uncertain events followed by rejection, conflict, annoying, meaningful, celebration, and enjoying which had the lowest proportion of uncertain events (Figure 6). Proportion of uncertain statements was calculated by taking the number of uncertain statements for a specific event type over the total number of uncertain statements.

Figure 6

Situation Type by Proportion of Uncertain Events

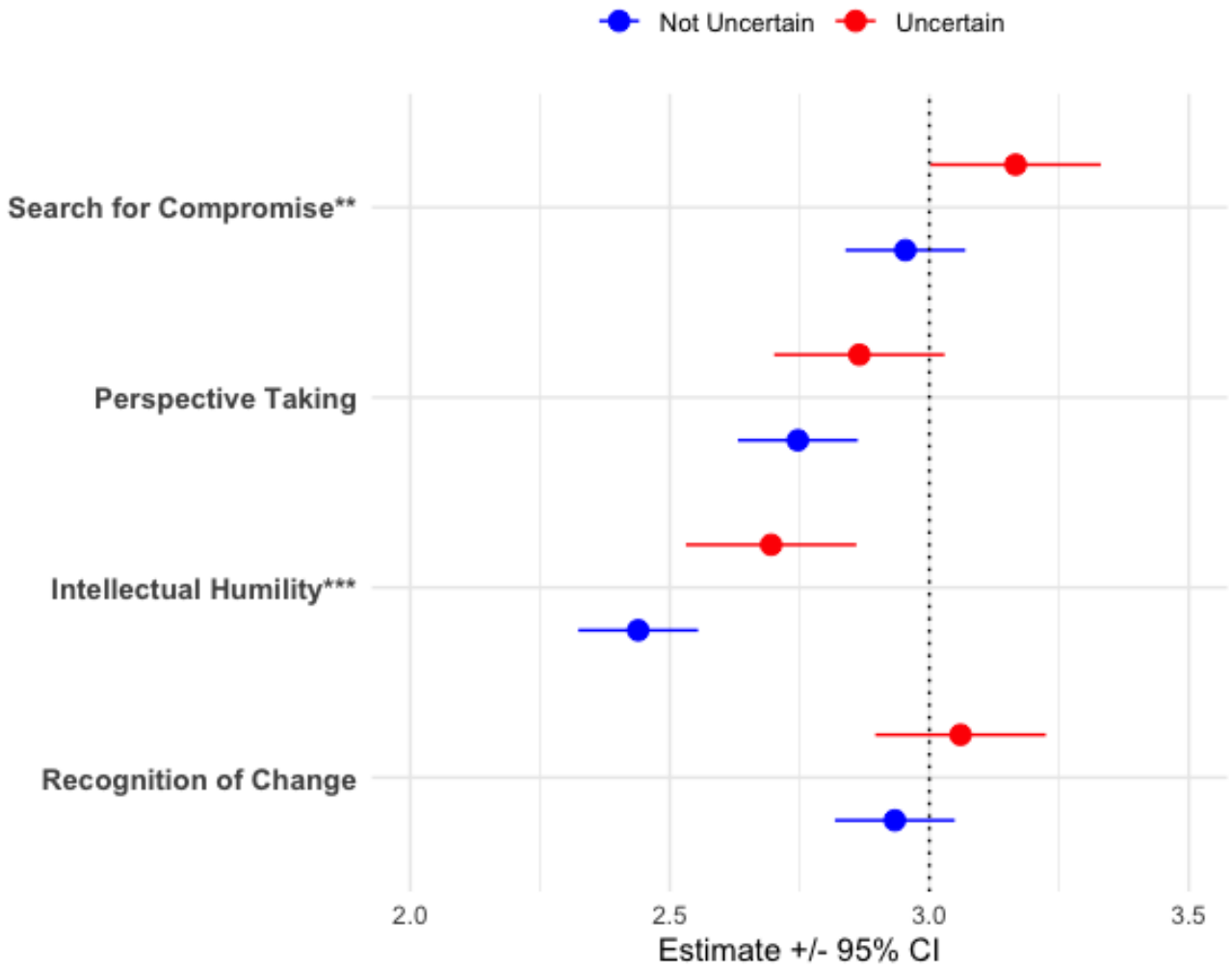


Do People Engage in Metacognitive Strategies When Uncertain?

To assess whether people engage in perspectival metacognition, I ran a linear mixed model with rating of each metacognitive feature as the dependent variable, metacognitive feature, uncertainty, and their interaction term as fixed effects predictors, and event type as a covariate with responses nested in participants. Perspectival metacognition was only measured when participants reported a negative event such as conflict, rejection, or annoying. There was a main effect of uncertainty, $F(1, 4550.8) = 19.04$, $p < .001$, and metacognitive feature, $F(3, 4355.1) = 64.47$, $p < .001$, but the interaction term for uncertainty and metacognitive feature was not significant, $F(3, 4355.1) = 0.88$, $p = .451$. This is a reasonably good model with an Akaike Information Criterion (AIC) of 13017.90 and a Bayesian Information Criterion of 13095.16. The AIC explains how well the model fits the data and generally rewards complexity while the BIC penalizes complexity to prevent overfitting. The fixed effects predictors explained about 4.7% of the variance ($R^2 = .047$) on metacognitive rating while the total variance (fixed + random effects) explained 44% of the variance on metacognitive rating ($R^2 = .440$). After examining the post-hoc pairwise contrasts (using Tukey method correction for multiple testing), I found that participants were more likely to engage in intellectual humility and a search for compromise for uncertain events compared to not uncertain events, but not a recognition of change or perspective-taking. The results are displayed in Figure 7.

Figure 7

Engagement in Perspectival Metacognition for Uncertain Versus not Uncertain Statements



Note. The dotted line represents the mid-point of the scale which ranges from 1-5. * $p < .05$, ** $p < .01$, *** $p < .001$.

State and Trait Effect of Uncertainty on Metacognition

For the state and trait effects of uncertainty on metacognition, again I ran a linear mixed model with metacognitive rating as the dependent variable, state uncertainty, trait uncertainty, metacognitive feature, and the interaction between metacognitive feature and state and trait

uncertainty as fixed effects predictors, event type as a covariate term, and responses nested in participants. Participants who reported more uncertain events were more likely to report engaging in intellectual humility, perspective taking, and a search for compromise. Moreover, the more uncertain an event was than one's typical events, the more likely one was to engage in intellectual humility, search for compromise, and recognize change. Table 6 displays the Anova statistics and model fit. Figures 8 and 9 display the change in metacognitive rating as a function of trait and state uncertainty respectively.

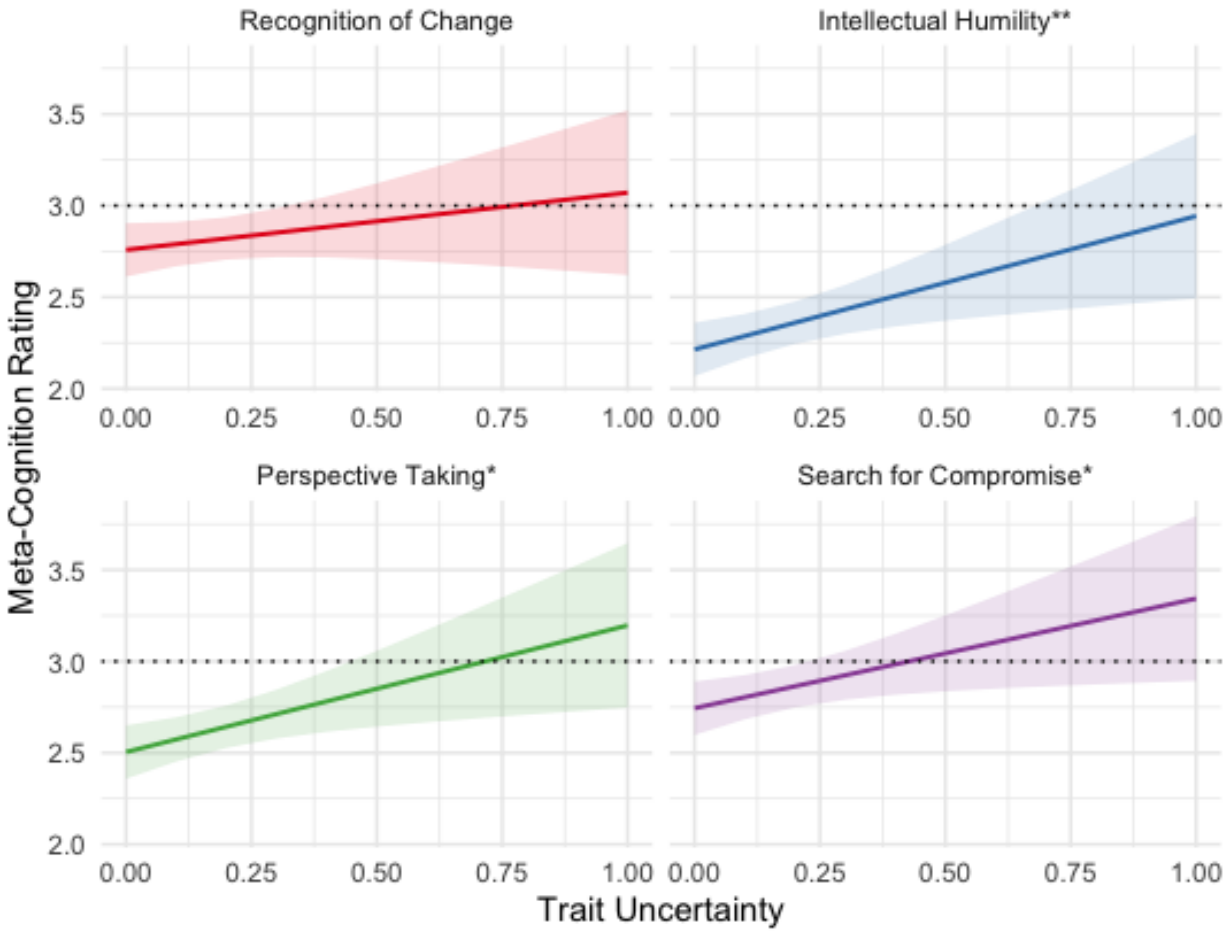
Table 6

Omnibus Anova Analyses and Model Fit for the Effect of Trait and State Uncertainty on Metacognition

	F value	Numerator *df*	Denominator *df*	*p*-value
Trait uncertainty	5.99	1	250.30	.015
State Uncertainty	16.10	1	4352.40	< .001
Trait Uncertainty x Metacognitive feature	1.79	3	4351.80	.146
State Uncertainty x Metacognitive feature	0.93	3	4351.80	.426
Model Fit				
AIC	13022.381			
BIC	13125.405			
R^2 (fixed effects)	.057			
R^2 (total)	.443			

Figure 8

Simple Slopes of Trait Uncertainty on Metacognitive Rating



Note. Recognition of Change: $b = 0.31$, $z = 1.17$; Intellectual Humility: $b = 0.73$, $z = 2.72$; Perspective Taking: $b = 0.69$, $z = 2.59$; Search for Compromise: $b = 0.60$, $z = 2.24$. * $p < .05$, ** $p < .01$, *** $p < .001$. The dotted line represents the mid-point of the scale which ranges from 1-5.

Figure 9

Simple Slopes of State Uncertainty on Metacognitive Rating



Note. Recognition of Change: $b = 0.19$, $z = 2.30$; Intellectual Humility: $b = 0.22$, $z = 2.66$; Perspective Taking: $b = 0.05$, $z = 0.58$; Search for Compromise: $b = 0.21$, $z = 2.49$. * $p < .05$, ** $p < .01$, *** $p < .001$. The dotted line represents the mid-point of the scale which ranges from 1-5.

What About Other Metacognitive Strategies Like Self-distancing?

I also examined the relationship between uncertainty and self-distancing. Self-distancing was measured for all event types. All four self-distancing item scores were averaged and used for

the analysis. I ran a linear mixed model with self-distancing as the dependent variable, uncertainty as the fixed effect predictor, event type as the covariate, and responses nested in participants. Participants were significantly more likely to engage in self-distancing when statements were coded as uncertain (M = 2.27, SE = 0.04) compared to not uncertain (M = 1.98, SE = 0.03), b = 0.29, SE = 0.03, $p < .001$.

Do Emotions Moderate the Relationship Between Uncertainty and Metacognition?

To assess whether emotions moderate the relationship between uncertainty and metacognition, I ran a linear mixed model with rating of each metacognitive feature as the dependent variable, metacognitive feature, uncertainty, affective disbalance (difference in positive and negative emotions) and respective interaction terms as fixed effects predictors, event type as a covariate, and responses nested in participants. I calculated affective disbalance by taking the average of positive (i.e., happy, calm, excited, and joyful) and negative emotions (i.e., sad, blue, anxious, angry, afraid, annoyed) and calculating their difference (average of negative emotions - positive emotions). I examined how the metacognitive rating differs across uncertain versus not uncertain statements and the metacognitive features at one standard deviation below and above the mean affective disbalance score. Since the difference was calculated by taking negative minus positive average, 1 *SD* below the mean represents relatively more positive emotions and 1 *SD* above the mean represents more negative emotions.

I observed a main effect of uncertainty, $F(1, 4534.3) = 55.85$, $p < .001$, metacognitive feature, $F(3, 4326.8) = 19.31$, $p < .001$, and affective disbalance, $F(1, 4472.5) = 12.96$, $p < .001$. The two-way interaction between uncertainty and metacognitive feature was not significant, p = .511, but the interaction between uncertainty and affective disbalance was significant, $F(1, 4528.4) = 37.13$, $p <.001$, as well as the interaction between metacognitive feature and affective

disbalance, $F(3, 4326.8) = 7.40$, $p < .001$. The three-way interaction term for uncertainty, metacognitive feature, and difference in emotions was not significant, $p = .345$.

When examining the post-hoc pairwise contrasts (using Tukey method correction for multiple testing), I found that when affective disbalance was low (-1 *SD*), participants were more likely to engage in a recognition of change, intellectual humility, perspective-taking, and a search for compromise. However, this effect disappears when affective disbalance was high (+1 *SD*). Also, when emotions are more positive (-1 *SD*), participants were more likely to engage in metacognitive reasoning for statements that are coded as uncertain compared to not uncertain. The results are displayed in Table 7 and Figure 10.

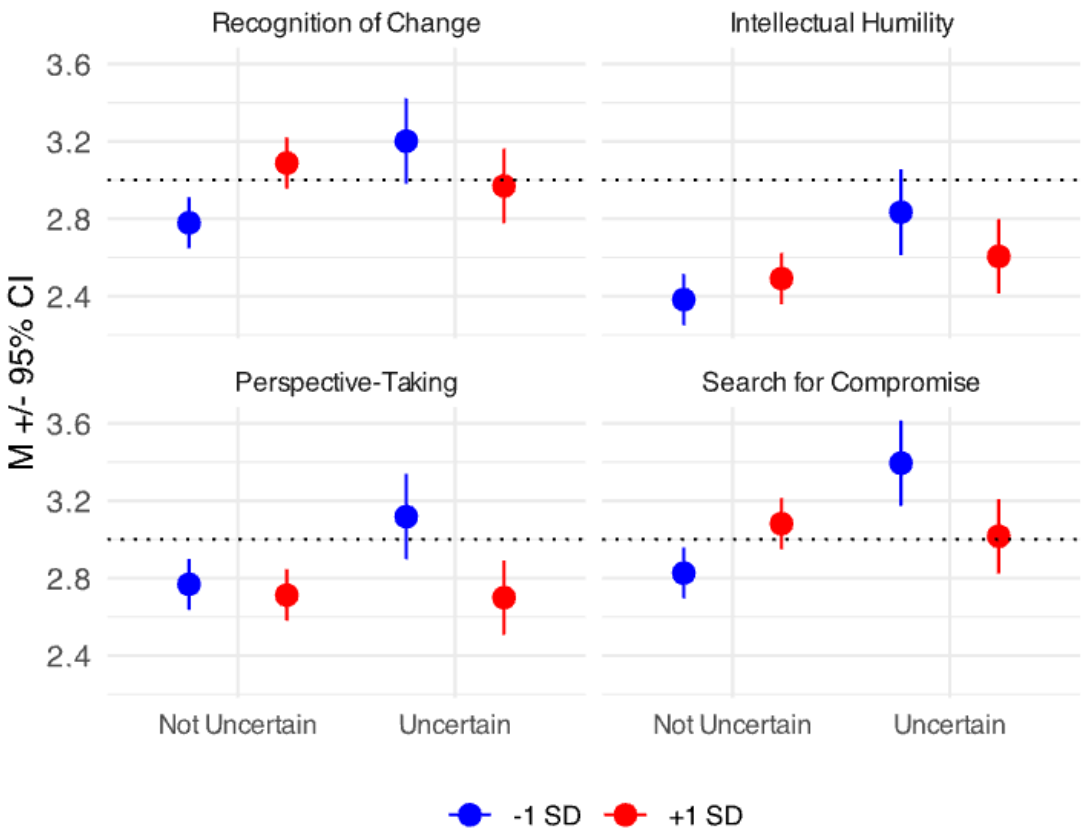
Table 7

Model Fit and Simple Effects of Uncertainty for Features of Metacognition as a Function of Affective Disbalance

Dependent Variable	Moderator Value (Affective Disbalance)	Not Uncertain *M* (*SE*)	Uncertain *M* (*SE*)	|*z*|	*p*-value
Intellectual humility	Low (-1 *SD* + *M*)	2.38 (0.07)	2.83 (0.11)	4.12	< .001
	High (+1 *SD* + *M*)	2.49 (0.07)	2.61 (0.09)	1.21	.227
Perspective taking	Low (-1 *SD* + *M*)	2.77 (0.07)	3.12 (0.11)	3.19	.001
	High (+1 *SD* + *M*)	2.71 (0.07)	2.70 (0.09)	0.14	.891
Recognition of change	Low (-1 *SD* + *M*)	2.78 (0.07)	3.20 (0.11)	3.85	< .001
	High (+1 *SD* + *M*)	3.09 (0.07)	2.97 (0.09)	1.25	.211
Search for compromise	Low (-1 *SD* + *M*)	2.83 (0.07)	3.39 (0.11)	5.18	< .001
	High (+1 *SD* + *M*)	3.08 (0.07)	3.02 (0.09)	0.69	.492
Model Fit					
AIC	12961.99				
BIC	13090.68				
R^2 (fixed effects)	.06				
R^2 (total)	.44				

Figure 10

The Effect of Metacognitive Feature, Uncertainty, and Affective Disbalance on Metacognitive Rating



CHAPTER FOUR: Discussion

In my thesis, I aimed to examine how uncertainty is perceived in general, for which situations uncertainty is perceived the most (positive, negative, or neutral), and finally the metacognitive strategies that individuals engage in when encountering uncertainty. To answer these questions, I employed a novel method by coding open-ended responses as uncertain and not uncertain using few-shot-prompted LLM-based classification (Stavropoulos et al., 2024).

First, I found that the few-shot GPT method was the most reliable way to classify uncertainty in daily life event reports, had a great accuracy score and did not overgeneralize too much but also did not miss many statements that were uncertain. This is an important combination as it vouches for the accuracy and precision of LLMs parallel to human coders for classifying complex psychological phenomenon. I also established criterion validity for it. Statements classified as uncertain were associated with higher emotional ambivalence and greater reports of feeling unsure compared to statements classified as not uncertain suggesting that statements classified as uncertain were perceived as uncertain by participants. Zero-shot classification also had good reliability and accuracy with $\kappa > .60$, ICC scores greater than .75 and accuracy above .80 which is very comparable to the few-shot GPT model. Interestingly, some of the zero-shot models like the open-source model had better sensitivity than the few-shot GPT model suggesting that it does not overgeneralize and may be tighter models. However, they were low on specificity, so they missed some statements that were uncertain.

Previous literature found that the GPT based LLMs are excellent at classifying emotions (Rathje et al., 2024) and metacognitive features like perspective taking (Stavropoulos et al., 2024). In this thesis, I found that the GPT models especially the few-shot GPT model is excellent at classifying uncertainty experienced by individuals in daily life. This suggests that LLMs can

classify increasingly complex constructs with excellent precision. Compared to general valence and discrete emotions such as "anger," uncertainty is a much more challenging construct because of the various language that is used to express it including emotions (e.g., anxious, worried), phrases (e.g., "I'm not sure"), and questions. Additionally, some questions such as rhetorical questions can be mistaken as uncertain when they are not. Even human coders initially had trouble classifying uncertainty speaking to its complexity and challenge. Considering the LLMs were able to accurately classify uncertainty suggests that it is improving and scaling in its ability to classify complex and challenging constructs. I discuss the implications for this in the Limitations, Future Directions, and Implications section below.

Second, I examined demographics and who was more likely to be uncertain. I found that females were more likely to report uncertain events than males. Uncertain events were also associated with greater negative affect and lower positive affect. This is in alignment with previous literature which found that uncertainty is generally perceived as aversive (Anderson et al., 2019; Morse et al., 2024). Consistent herewith, negative events such as sad or bad news, conflict, rejection, and annoying were more likely to be uncertain, whereas positive (enjoying or celebration) or neutral (meaningful) events were less likely. These observations dovetail with the uncertainty intensification hypothesis which suggests that uncertainty tends to amplify negative affect if it is unpleasant or positive affect if it's pleasant (Bar-Anan et al., 2009).

Uncertain events were generally challenging, negative, less predictable, and in the hands of other people. Both trait and state uncertainty were also associated with an increased perception of the event being challenging, negative, in the hands of other people, and less predictable. These results are in alignment with previous literature. The uncertainty management theory states that how one manages uncertainty depends on how they perceive it and whether it is

harmful or beneficial to oneself. In this study, participants perceived situations coded as uncertain to be more harmful to themselves (Brashers et al., 2000). This is in alignment with literature explaining the aversive nature of uncertainty (Hirsh et al., 2012; Hogg, 2000). If uncertainty is perceived as negative, challenging, less predictable, or out of one's control, it makes sense that one would be averse and would be motivated to avoid it. This study adds a contextual nuance to the fact that uncertainty is aversive because it is aversive for specific situations or on the state level but also on the trait level such that there is also a stable perception of uncertainty as being aversive.

Self-distancing was measured for all event types and participants were more likely to engage in self-distancing for uncertain events compared to not uncertain events. This observation dovetails with the literature suggesting that engaging in self-distancing can help one to reduce negative emotion and help make meaning out of negative emotion (Kross & Ayduk, 2011). Moreover, participants were more likely to engage in metacognitive strategies like intellectual humility and a search for compromise for uncertain events. Notably, these latter inferences only apply to negative event types because perspectival metacognitive strategies were only measured when participants indicated experiencing a negative event type (i.e., conflict, annoying, and rejection).

Since uncertain events were also perceived as negative, challenging, and out of one's control, engaging in intellectual humility may be one way to reduce uncertainty by seeking others' opinion and information from other people. Searching for a compromise may also be a way to reduce the uncertainty by integrating multiple viewpoints or finding one solution. Previous literature found that effects of uncertainty on social and political behaviour is context-dependent such that uncertainty was more likely to increase support for compromise when

people did not feel threatened or uncertainty was associated with positive or neutral emotion. However, uncertainty was more likely to decrease support for compromise when people felt threatened (Haas, 2016).

Additionally, previous literature also suggests that when people find uncertainty to be personally threatening, they are less likely to exhibit intellectual humility and more likely to stick to comforting beliefs and unambiguous truths (Porter et al., 2022). For example, one study demonstrated that when politicians felt threatened – whether that threat was to the self, group, or system – they had higher scores on closed-mindedness and political conservatism than politicians in the control group (Thórisdóttir & Jost, 2011). Thus, threat appears to be moderating the relationship between uncertainty and metacognitive reasoning and the fact that participants in this study engaged in greater intellectual humility and a search for compromise suggests that they did not feel threatened by it.

To test this hypothesis, I conducted an additional analysis with threat as the moderator, uncertainty as the predictor and metacognitive reasoning as the dependent variable. The extra analysis is in Appendix B, Figure B1. I found that at lower levels of threat, participants were more likely to engage in metacognitive reasoning, but this effect disappeared at higher levels of threat. Additionally, at lower levels of threat, metacognitive reasoning was higher for statements coded as uncertain compared to not uncertain. I found the same pattern of results for the negativity appraisal (Figure B2) and affective disbalance where greater positive affect was associated with greater engagement in metacognition, but this effect disappeared for greater negative affect. Also, for greater positive affect, people were more likely to engage in metacognitive reasoning for statements coded as uncertain compared to not uncertain. This

suggests that when people perceive higher levels of threat, negativity, or negative affect when experiencing uncertainty, they are less likely to engage in metacognitive reasoning.

Further, many of the uncertain and negative events were conflict type events (n = 384) compared to rejection (n = 116) or annoying (n = 300) events; thus, engaging in intellectual humility and searching for a compromise may be strategies that are best used to deal with uncertainty experienced as a result of the most frequently endorsed negative events in the study, such as conflict and annoying events rather than other types of negative events like rejection.

Limitations, Future Directions, and Implications

Although I used an automated LLM-based system for classifying uncertainty in spontaneous, unstructured reports, the other questionnaires such as the event dimension scale or state threat and challenge questionnaire were self-reports. Participant ratings from these questionnaires are subject to the same biases as self-reports such as the social desirability bias or memory biases. Although, there is less chance of the recall bias occurring because participants reported on the questionnaires immediately after reporting on the event, participants' ratings on the questionnaires may be strongly influenced by their emotional state. Depending on the event reported and the emotional state one is in, it could have biased their ratings on the other questionnaires or intensified their ratings.

Another limitation is that the SWiS scale which captures perspectival metacognition was only shown to participants if they reported a negative event; therefore, it is unclear whether people engage in metacognitive reasoning when uncertain about positive event types. Although, most of the uncertain events were regarding negative events such as conflict, rejection, or annoying type event, it excludes the sad or bad news category which was the event type reported with the highest proportion of uncertain statements. Additionally, it would be ideal to include the

SWiS scale for all event types to compare engagement in metacognitive strategies for all event types.

Further, there was no random assignment to uncertain versus not uncertain conditions in this study since this was not an experimental study. One future avenue is to experimentally manipulate uncertainty to assess which metacognitive strategies people engage in when uncertain and how they perceive uncertainty. Future studies can conduct an experimental design where uncertainty can be manipulated in a positive, negative, and neutral context and experimenters can assess how people appraise the uncertainty and examine the metacognitive strategies they engage in. Additionally, manipulating uncertainty in a positive context can shed light on how individuals appraise uncertainty in a positive context and whether they try to reduce it or maintain it.

Another future scope for this work is to examine cross-sectional associations between uncertain versus not uncertain statements and appraisals or metacognitive reasoning in different cultures or populations. The current sample is recruited from North America which limits the generalizability of the findings to North Americans. How might these results differ across populations from Europe, Africa, and Asia? There is some evidence suggesting that people from the East have a more holistic and dialectical approach to thinking making them more accepting of uncertainty (Nisbett, 2003). Thus, it would be interesting to compare the perceptions of uncertainty between Easterners and Westerners and compare how they navigate uncertainty in terms of the metacognitive strategies in which they engage in.

Another future direction is examining if engaging in these metacognitive strategies increase well-being over time. Engaging in metacognitive reasoning or strategies might be an adaptive solution to navigating uncertainty. By testing the effects of metacognitive engagement on well-being, one can assess the effectiveness and adaptiveness of these strategies. If engaging

in these strategies improves well-being at one point in time and over time, these strategies may be implemented in clinical literature as tools to deal with uncertainty and anxiety disorders which are characterized by a fear of the unknown (Carleton, 2016a). Current treatment of anxiety disorders focuses on acceptance or tolerance of the cognitions and symptoms as suggested by acceptance and commitment therapy (Arch & Craske, 2008). Cognitive-behavioural therapy offers cognitive restructuring which involves modifying the thought content to make it less threatening (Arch & Craske, 2008). Both involve metacognitive processes through self-monitoring but involve a focus on the self and one's cognition. The metacognitive strategies proposed here can allow one to shift their focus to others or outside of themselves by considering the opinions of others or perspectives of others. This has implications for improving mental health and potentially informing new therapies involving metacognitive strategies.

Further, this research has implications for the judgment and decision-making literature because it expands our understanding of the strategies and heuristics used to make decisions under uncertainty in daily life. The results can be applied to medical, legal, financial, educational, and other sectors where uncertainty appraisals determine one's metacognitive regulation strategy. This work also has implications for cognitive-emotion theories informing the emotions and appraisals associated with uncertainty which is important for research on emotion regulation. For example, Gross's extended process model of emotion regulation suggests that people identify emotions, select regulation strategies, and implement them (Gross, 2015). My work highlights that people engage in a meta-appraisal of uncertainty, which is generally associated with negative emotions, and they engage in downstream metacognitive strategies (i.e., intellectual humility, search for compromise, self-distancing) which may be considered emotion regulation strategies since people are more likely to engage in them for uncertain events

(associated with greater negative affect) compared to not uncertain events. Thus, my work highlights the process of emotion regulation for uncertainty.

Finally, this research also has implications for the broader field of research methods in psychology demonstrating the ability of AI to capture complex and challenging psychological phenomenon such as uncertainty (Feuerriegel et al., 2025; Rathje et al., 2024; Stavropoulos et al., 2024). The research pipeline may inform future work involving uncertainty or other complex phenomenon where coding by humans is either not feasible or prohibitively costly. LLMs can also be easily fine-tuned allowing for constant precision and accuracy in results. Classification via LLMs can be applied to qualitative studies, research involving social media to analyze posts, clinical psychology to analyze text for symptoms of a disorder or emotional state and much more.

Conclusion

Uncertainty is an inevitable part of most facets of life. Generally, people either avoid uncertainty or embrace it depending on how they appraise it. In this thesis, I found that the uncertainty people report in daily life tends to be perceived as negative, challenging, out of one's control, and associated with greater negative affect. To navigate this uncertainty, people engage in metacognitive strategies such as intellectual humility, a search for compromise and self-distancing.

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Appendix A

Table A1

Definition of Uncertainty Across Various Fields

Field	Representative citation	Definition of uncertainty	Similarities across the fields
Judgment and Decision-Making (JDM)	Kahneman & Tversky (1982) Ülkümen et al (2016)	JDM literature focuses on the outcomes of uncertainty. Uncertainty is defined as something that can be expressed through probability and confidence statements. Distinguishes internal uncertainty caused by ignorance versus external uncertainty caused by the environment where something cannot be determined due to the nature of the situation (e.g., winner of political election)	Lack of information Unknown probabilities or unable to predict what will happen
Clinical	Carleton (2016b)	The perceived absence of salient, key, or sufficient information. Note that this is distinguished from ambiguity which is described as conflicting information.	
Cognitive-emotion theories	Smith & Ellsworth (1985) Yeo & Ong (2024)	Uncertainty is about how well one is able to understand what is happening in a situation and predict what will happen next.	

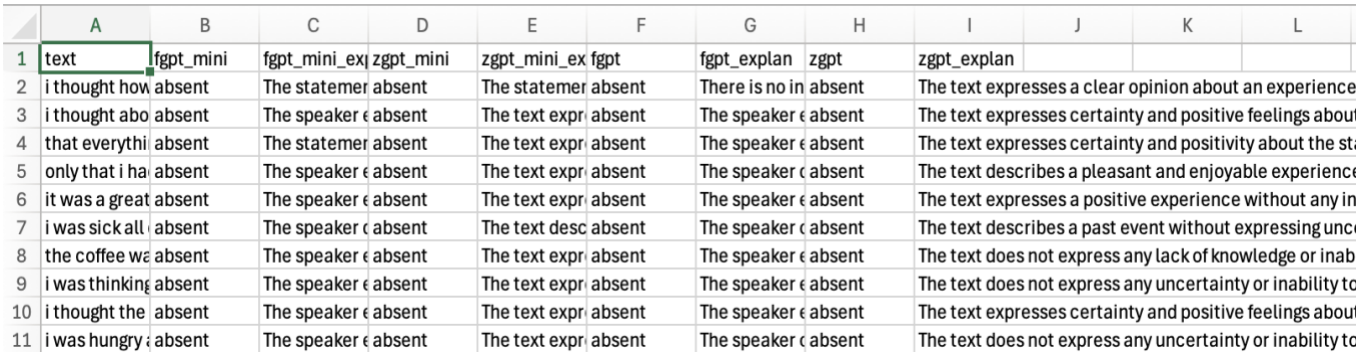
Table A2

Examples of Input in AI Coder

Present		
Example 1	Example 2	Example 3
I was thinking about how I didn't know all the people hanging out. I was worried that I would come off as weird or awkward. I was unsure if I wanted to go at all.	I had an argument with my girlfriend that still has me confused as to what we were really fighting about in the first place.	I'm not sure how long it'll take to learn the guitar, but I'm really enjoying the process, and I can't wait to play my first song!
Explanation 1	Explanation 2	Explanation 3
The speaker expressed not knowing all the people and being unsure of whether they want to attend in alignment with the definition demonstrating uncertainty.	The speaker expressed confusion which indicates not understanding what the fight is about demonstrating uncertainty.	The speaker indicates being unsure and unable to predict how long it will take them to play the guitar.
Absent		
Example 1	Example 2	Example 3
I thought it was fun and cool.	My niece called me out of the blue to see what I was doing later. She dropped by to see me after school. I enjoyed her.	Every driver slows down at a green light here. Is it too much to ask to just keep moving?
Explanation 1	Explanation 2	Explanation 3
There is no indication of a lack of understanding or not being able to predict what will happen. Instead it is a clear and positive opinion.	The speaker expresses an enjoyable event and there is no lack of knowledge or understanding and nothing that is not predictable.	The speaker asks a question, but it is rhetorical in nature meaning they are not actually seeking a answer or clarification and neither is anything unpredictable. Rather it has underlying feelings of frustration.

Figure A1

Output File of AI Coder



	A	B	C	D	E	F	G	H	I	J	K	L
1	text	fgpt_mini	fgpt_mini_ex	zgpt_mini	zgpt_mini_ex	fgpt	fgpt_explan	zgpt	zgpt_explan			
2	i thought how	absent	The statemer	absent	The statemer	absent	There is no in	absent	The text expresses a clear opinion about an experience			
3	i thought abo	absent	The speaker e	absent	The text expr	absent	The speaker e	absent	The text expresses certainty and positive feelings about			
4	that everythi	absent	The statemer	absent	The text expr	absent	The speaker e	absent	The text expresses certainty and positivity about the st			
5	only that i ha	absent	The speaker e	absent	The text expr	absent	The speaker c	absent	The text describes a pleasant and enjoyable experience			
6	it was a great	absent	The speaker e	absent	The text expr	absent	The speaker e	absent	The text expresses a positive experience without any in			
7	i was sick all	absent	The speaker c	absent	The text desc	absent	The speaker c	absent	The text describes a past event without expressing unc			
8	the coffee wa	absent	The speaker e	absent	The text expr	absent	The speaker e	absent	The text does not express any lack of knowledge or inab			
9	i was thinking	absent	The speaker e	absent	The text expr	absent	The speaker e	absent	The text does not express any uncertainty or inability to			
10	i thought the	absent	The speaker e	absent	The text expr	absent	The speaker e	absent	The text expresses certainty and positive feelings about			
11	i was hungry a	absent	The speaker e	absent	The text expr	absent	The speaker c	absent	The text does not express any uncertainty or inability to			

Note. *f* represents few-shot and *z* represents zero-shot with the model's name beside it. Beside each column of present and absent, there is a column with the explanation of the classification.

Appendix B: Supplementary Analyses

Threat and Metacognitive Reasoning

To conduct this analysis, I used one item from the State Challenge and Threat Questionnaire on threat ("When I faced this situation, I felt threatened and afraid") rated on a scale of 1 (not at all) to 5 (definitely). I used a linear mixed model with metacognitive rating as the dependent variable, metacognitive feature, uncertainty, threat item and their interaction as fixed effects predictors, event type as the covariate and responses nested in participants. There was a main effect of uncertainty, $F(1, 4531) = 44.84$, $p < .001$, meta-cognitive feature, $F(3, 4333.4) = 17.26$, $p < .001$, and threat $F(1, 4590.4) = 76.88$, $p < .001$. The two-way interaction between uncertainty and metacognitive feature was not significant, $p = .561$ as well as the interaction between metacognitive feature and threat, $p = .272$, but the interaction between uncertainty and threat was significant, $F(1, 4552.8) = 29.18$, $p < .001$. The three-way interaction term for uncertainty, meta-cognitive feature, and threat was not significant, $p = .514$. However, when examining the post-hoc pairwise contrasts (using Tukey method correction for multiple testing), I found that for lower threat levels (-1 SD), participants were more likely to engage in a recognition of change, intellectual humility, perspective-taking, and a search for compromise but this effect disappears at higher levels of threat (+1 SD). Also, when threat is low (-1 SD), participants were more likely to engage in metacognitive reasoning for statements that are coded as uncertain compared to not uncertain. The statistics are reported in Table B1 and the results are displayed in Figure B1.

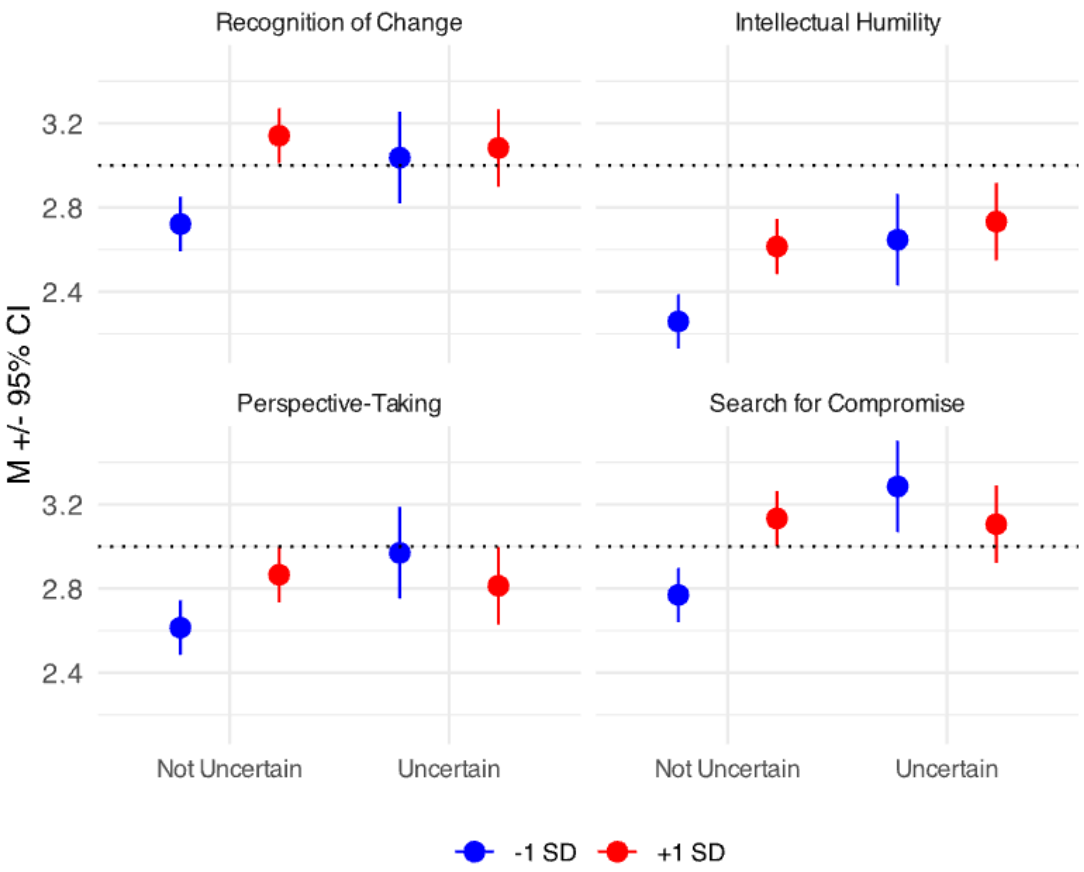
Table B1

Model Fit and Simple Effects of Uncertainty for Features of Metacognition as a Function of Threat

Dependent Variable	Value of moderator	Not Uncertain *M* (*SE*)	Uncertain *M* (*SE*)	|*z*|	*p*-value
Intellectual humility	Low (-1 *SD* + *M*)	2.26 (0.07)	2.65 (0.11)	3.59	< .001
	High (+1 *SD* + *M*)	2.61 (0.07)	2.73 (0.09)	1.28	.199
Perspective taking	Low (-1 *SD* + *M*)	2.61 (0.07)	2.97 (0.11)	3.28	.001
	High (+1 *SD* + *M*)	2.87 (0.07)	2.81 (0.09)	0.57	.569
Recognition of change	Low (-1 *SD* + *M*)	2.72 (0.07)	3.04 (0.11)	2.91	.004
	High (+1 *SD* + *M*)	3.14 (0.07)	3.08 (0.09)	0.63	.526
Search for compromise	Low (-1 *SD* + *M*)	2.77 (0.07)	3.28 (0.11)	4.76	< .001
	High (+1 *SD* + *M*)	3.13 (0.07)	3.11 (0.09)	0.30	.766
Model Fit					
AIC	12952.88				
BIC	13081.61				
R^2 (fixed effects)	.06				
R^2 (total)	.44				

Figure B1

The Effect of Uncertainty by Threat on Metacognitive Reasoning



Negativity and Metacognitive Reasoning

To conduct this analysis, I used the negativity appraisal from the event dimension scale. I ran a linear mixed model with metacognitive rating as the dependent variable, metacognitive feature, uncertainty, negativity, and their interaction as fixed effects predictors, event type as the covariate and responses nested in participants. There was a main effect of uncertainty, $F(1, 4436.8) = 12.84$, $p < .001$ and meta-cognitive feature, $F(3, 4234.8) = 6.43$, $p < .001$, but negativity was not significant, $p = .076$. The two-way interaction between uncertainty and metacognitive feature was not significant, $p = .710$, but the interaction between uncertainty and

negativity was significant, $F(1, 4431) = 5.96$, $p = .015$, as well as the interaction between metacognitive feature and uncertainty $F(3, 4234.8) = 8.88$, $p < .001$. The three-way interaction term for uncertainty, meta-cognitive feature, and threat was not significant, $p = .787$. However, when examining the post-hoc pairwise contrasts (using Tukey method correction for multiple testing), I found that for lower negativity (-1 *SD*), participants were more likely to engage in a recognition of change, intellectual humility, perspective-taking, and a search for compromise but this effect disappears at higher ratings of negativity (+1 *SD*). Also, when negativity is low (-1 SD*),* participants were more likely to engage in metacognitive reasoning for statements that are coded as uncertain compared to not uncertain. The statistics are reported in Table B2 and the results are displayed in Figure B2.

Table B2

Model Fit and Simple Effects of Uncertainty for Features of Metacognition as a Function of Negativity

Dependent Variable	Value of moderator	Not Uncertain *M* (*SE*)	Uncertain *M* (*SE*)	|*z*|	*p*-value
Intellectual humility	Low (-1 *SD* + *M*)	2.43 (0.08)	2.89 (0.14)	3.24	.001
	High (+1 *SD* + *M*)	2.45 (0.06)	2.63 (0.09)	1.86	.063
Perspective taking	Low (-1 *SD* + *M*)	2.87 (0.08)	3.07 (0.14)	1.44	.150
	High (+1 *SD* + *M*)	2.69 (0.06)	2.79 (0.09)	1.10	.269
Recognition of change	Low (-1 *SD* + *M*)	2.76 (0.08	3.11 (0.14)	2.50	.013
	High (+1 *SD* + *M*)	3.03 (0.06)	3.06 (0.09)	0.30	.761
Search for compromise	Low (-1 *SD* + *M*)	2.83 (0.08)	3.18 (0.14)	2.47	.014
	High (+1 *SD* + *M*)	3.02 (0.06)	3.17 (0.09)	1.60	.110
Model Fit					
AIC	12734.31				
BIC	12862.60				
R^2 (fixed effects)	.05				
R^2 (total)	.44				

Figure B2

The Effect of Uncertainty by Negativity Appraisal on Metacognitive Reasoning

