Making Decisions with Limited Information:

Forming and Updating

Ambiguous Beliefs

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ABSTRACT

Introduction: How individuals deal with outcomes under unknown risks (I.e. ambiguity) can be important for understanding decisions in the real world. One commonly applied model for ambiguous decisions, maxmin expected utility (MMEU), suggests that people only focus on the range of probabilities. However, other models, including subjective recursive expected utility (SREU), suggest that instead of thinking about the range, people construct a belief about the probabilities as a distribution, based on their experiences or intuition. MMEU has been used to relate ambiguity preferences to clinical disorders, including autism spectrum disorder. However, if SREU models are a better reflection of decisions under ambiguity, these differences may be related to beliefs instead of preferences. **Methods**: To investigate the role of beliefs in ambiguous decisions, we collected choice and personality data from an online sample (N=298) utilizing a novel task. In our task, participants make decisions under ambiguity after learning about the distribution of probabilities during a previous decision task. We test if variance in beliefs influences decisions under ambiguity, interacts with reward feedback, and accounts for individual differences related to a clinical variable, the Autism Quotient (AQ) to explore the bounds of the MMEU model. **Results:** Participants preferred ambiguous stimuli associated with high variance distributions and made larger changes in response to feedback information when applied to high variance distributions. We did not replicate results showing that ambiguity aversion decreased with AQ but did find AQ decreased with the believed variance of probabilities. **Conclusions**: Our results provide experimental evidence that decisions under ambiguity are influenced by beliefs, violating a key axiom of MMEU, suggesting previous results should be revisited by incorporating beliefs to better understand the mechanisms of ambiguous choice.

DEDICATIONS

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CHAPTER 1:
INTRODUCTION

Day-to-day decisions often must be made without full access to all available information. We are not told the probability of getting into a car crash when we let a friend drive us home late at night. If we lend money to a friend, we are not told the probability that they will pay us back in the next year. These kinds of decisions with no information about the probability are described as under a condition of ambiguity and has been related to how people decide to invest for their retirement (Dimmock, et al., 2016), how doctors decide treatment options (Portnoy et al., 2011), as well as decisions people make about their careers (Xu & Adams, 2020). How can one try to make rational decisions when they do not know the probability of the different outcomes?

Initially economists thought that under conditions of ambiguity people would assign a probability to different outcomes based on their experiences or some other principle (e.g. “I think there is a 50% chance that bob will pay me back my money next week like he said.”). However, one of the earliest empirical investigations, by Daniel Ellsberg, showed that this intuition was incorrect (Ellsberg, 1963). In a simplified version of Ellsberg's experiment, imagine you have an urn filled with ten balls that are either yellow or blue. You are then asked if you would prefer a bet where you win $10 for pulling a yellow ball out of the urn or flipping a coin heads up. You are then asked whether you would prefer a bet between flipping the same coin heads up or pulling a blue ball out of the urn.

Most participants strongly preferred flipping the coin over pulling both the blue and yellow ball. As the prize is the same no matter what participants should only prefer a bet if they think that winning is more likely. However, it cannot be that pulling a yellow and blue ball out of the urn are both less likely than the coin flip (50%) as those are the only colors in the urn. This preference for known risks (i.e., probability of an outcome) (Bernoulli, 1954) as compared to unknown risks, or ambiguity (Ellsberg, 1963; Jia et al, 2020)[1] became known as ambiguity aversion. In response, subsequent economic models of behavior then had to use different ways to accommodate ambiguity averse behavior.

The maxmin expected utility (MMEU) model (Gilboa and Schmeidler 1989) has now been used widely to understand ambiguity aversion, its neural correlates (Levy et al., 2010; Wu et al., 2021), and its relationship to individual differences including psychiatric disorders (Fujino et al., 2016; Raio et al., 2022**)**.MMEU managed to account for ambiguity averse behavior by describing a decision maker which is strictly concerned about the range of possible probabilities and adopting a preference for that range. This means that an ambiguity averse decision maker need not concern themselves with what they think might be in the urn but simply try to avoid the possibility of an unfavorable composition. However, it also means that a belief about the likely contents cannot influence their decisions either. By using this model of decision making,

1 Please note that ambiguity preferences (aversion or tolerance), as referenced throughout the text which describes choice behavior, is different from intolerance of uncertainty (Sexton & Dugas, 2009), a similarly named construct which is related to personality and clinical psychology as these constructs function independently of each other (Borozan, et al.,2022; Tanaka et al., 2015).

researchers have identified a number of psychological processes and individual differences that are related to ambiguity aversion.

Several studies have now been performed where individuals make choices between a prize of money with some range of probability and either some certain amount of money or money with some probability(Levy et al., 2012). In order to accept prizes under ambiguity with larger ranges, people require larger ambiguous prizes or alternative risky options to have lower probabilities of winning (Levy et al., 2010). The range has been shown to be encoded in the lateral PFC (prefrontal cortex) (Huettel et al., 2006) and related to the subjective value signal in the medial PFC (Levy et al., 2010). This evidence suggests that people use information about the range of probabilities when evaluating an ambiguous outcome.

A more contemporary model, the subjective recursive expected utility (SREU) model was able to incorporate both ambiguity averse behavior and allow individuals to construct a belief about the contents of the urn. Under SREU the belief is a distribution of probabilities rather than a single probability(Figure 1) and decisions are driven by preferences for the variance in that belief. In terms of the Ellsberg urn, this might look like believing about how its contents were constructed. If a coin was flipped and a blue ball entered for every head and a yellow ball for every tail, the most likely contents would be equal numbers of blue and yellow balls but some probability for more extreme contents. Researchers interested in whether human decisions reflect a process described by MMEU or

SREU have therefore focused on the role of beliefs in decisions under ambiguity (Halevy et al., 2007; Conte and Hey 2013; Borozan,et al., 2022). If beliefs about the distribution of probabilities do affect choices under ambiguity, it would falsify the MMEU model and suggests that the construction of beliefs are a key element of decisions under ambiguity, its neural correlates, and relationship to psychiatric disorders.

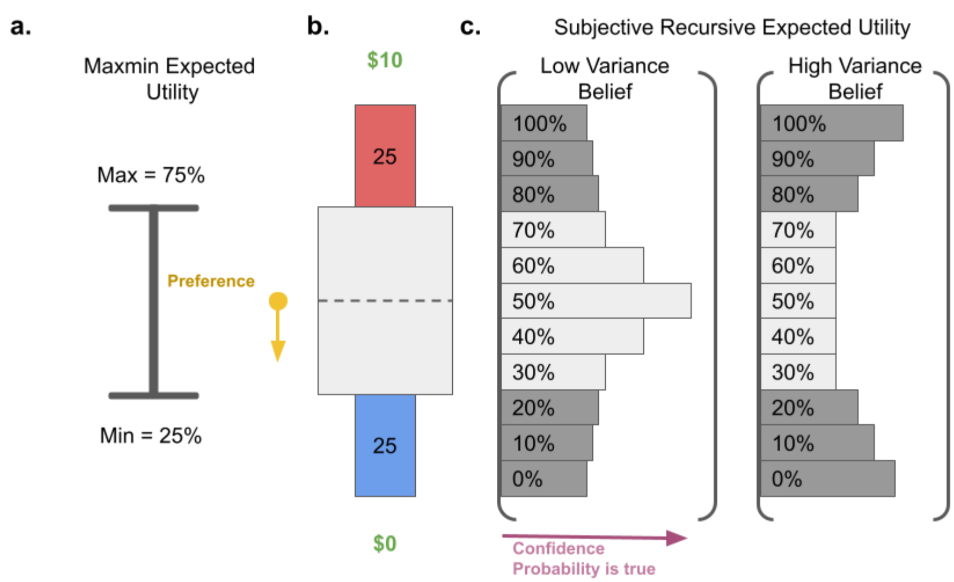

Figure 1. A diagram showing how a decision maker operating under MMEU and SREU might interpret a common stimulus used to represent ambiguous outcomes. **(a.)** An ambiguity averse decision maker using MMEU is concerned strictly with the range of probabilities treating ambiguous outcomes as though they have a probability at some constant ratio between 50% and the lower bound of the range (25% in this case). **(b.)** A hidden lottery stimulus commonly used for experiments on ambiguity aversion (Levy et al., 2012). The stimulus represents a bag where participants can win $10 for randomly pulling out a red chip and $0 for pulling a blue chip. The bag is filled with at least 25 red and 25 blue chips, but the color of the remaining 50 chips is

obscured by the gray box. **(c.)** A decision maker using SREU constructs a belief about the probability of winning $10 similar to the two histograms. The height of each gray box represents the probability that the given chance of winning is the true probability. The light gray boxes represent the parts of the belief covered by the range. The dark gray boxes are outside of the stated range.

The SREU model is relatively unexplored, however several experiments have provided circumstantial evidence that people incorporate a belief about probabilities as described by the model. First, when given an explicit description about the distribution of probabilities, people are averse to the variance - not the range - of that explicit distribution (Halevy et al., 2007, Danese et al., 2017, Chapman et al., 2023). Second, familiarity, which could decrease the variance in the believed distribution of probabilities, has been shown to counteract ambiguity aversion (Chew et al., 2008; Chew et al., 2012). Lastly, both explicit manipulations of the range and variance in the distribution of probabilities are encoded in the lateral PFC (prefrontal cortex) (Huettel et al., 2006, Bach et al., 2011). As manipulations of the range are confounded by an increased variance, but manipulations of the variance do not necessarily change the range, the lateral PFC may be encoding the variance in both cases. While these results are consistent with the SREU model and not MMEU, direct experimental evidence is necessary to show a causal relationship between beliefs and decisions under ambiguity to falsify the MMEU model.

Explanatory models such as MMEU and SREU are often tested through statistical model fitting, competition, and comparisons of the model's correlation coefficients (Piray et al., 2019) or the variance they account for (Wilson and Collins, 2019). Critically however, these kinds of comparisons cannot tell us whether key features of behavior are fundamentally incompatible with a particular class of decision models (e.g., Rutledge et al., 2010). Instead, these incompatibilities can be identified by testing the specific assumptions, or axioms, necessary for a model (Popper, 1959). This project proposes four tests of the assumption under MMEU that beliefs about the distribution of the probability do not influence choice (see Table 1). The first two tests are designed to demonstrate whether human choices under ambiguity are guided by beliefs about the distribution of probabilities, a key feature of SREU, which would violate major assumptions of MMEU. The latter two tests are designed to demonstrate the wider implications of this violation. We first extend these implications to another decision context, reinforcement learning, by demonstrating how the resolution of ambiguity given feedback is affected by the kinds of beliefs described by SREU. We also extend the implications of this violation to previous literature which used MMEU to link decisions under ambiguity to psychiatric disorders, by using autism as a case study. Evidence that the increased tolerance of ambiguity associated with autism under MMEU (Fujino et al., 2017) is driven by individual differences in beliefs about the probabilities would violate a key assumption of MMEU and suggest the model is not appropriate for linking decision behavior to psychiatric disorders.

The first two tests we propose attempt to implicitly manipulate subjective beliefs about the distribution of probabilities during decisions under ambiguity.

Previous experiments have shown that humans are averse to variance in an explicitly described distribution of probabilities (Halevy et al., 2007). However, because ambiguity is meant to reflect the absence of this explicit information, an implicit manipulation of subjective beliefs is needed to maintain the condition of ambiguity. Classically, one way similar beliefs can be formed is through using past experiences (Dayan and Daw, 2008). For example, if someone enters a gamble with an unknown chance of winning, they may use probabilities from previous gambles to inform their current choices. In this example, individuals may prepare for worse outcomes if they previously had either 10% or 90% chance of winning (high variance) compared to a situation where they consistently had 50% chance (low variance). If individuals' choices reveal an aversion to greater variance in experienced probabilities (see Figure 2), despite maintaining the same average probability, this would be a violation of MMEU, but would be consistent with ambiguity aversion under SREU.

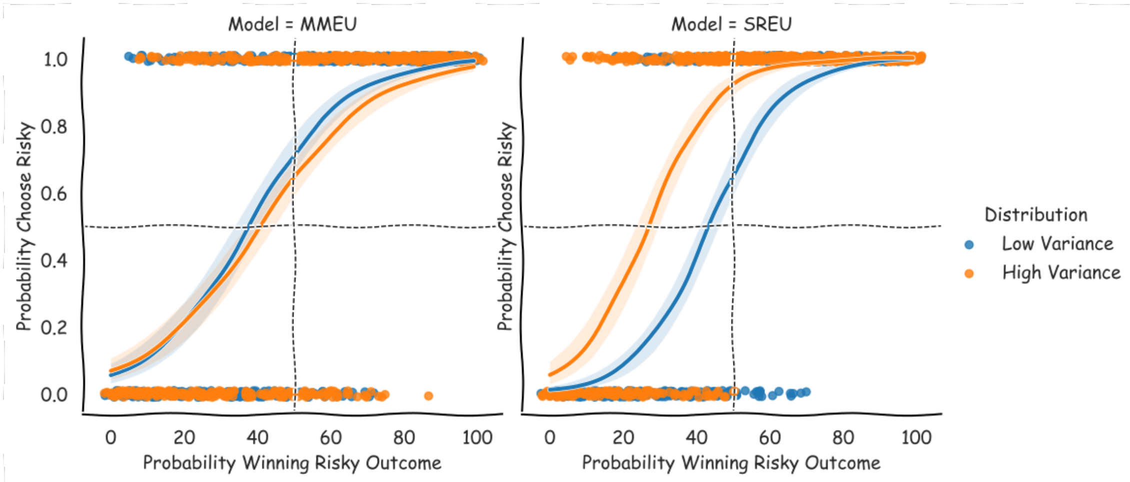

Figure 2. A simulation of ambiguity averse choices between ambiguous and risky outcomes with a given probability under both MMEU and SREU models. Under both models a decision-maker chooses between a risky lottery with the probability of winning some money described by the x-axis. The probability of choosing the risky over the ambiguous lottery with the same prize is described by the y-axis. The difference in choice behavior between the low and high variance ambiguous outcomes under SREU (on the right) represents a violation of MMEU (on the left).

Another way to implicitly manipulate beliefs about the distribution of probabilities relies on a principle from psychology and neuroscience called normalization (Laughlin, 1981; Schwartz and Simoncelli, 2001). Normalization refers to a coding scheme where values are encoded relative to other recent and related experiences rather than absolute terms and has been observed with many kinds of variables including brightness (Carandini and Heeger, 2011) and reward values (Louie et al., 2013). In particular, when making economic choices, items are perceived as more valuable when preceded by low value items (Cox and Kable, 2014; Khaw et al., 2017). Similarly, if the variance in probabilities is perceived as greater when preceded by periods of low variance in probabilities (Bhui et al., 2021) and results in more ambiguity averse choices, this would be a violation of MMEU, but again, would be consistent with SREU. Providing two experimental manipulations of individual's beliefs about the distribution of probabilities through direct experience and order effects (normalization), will allow us to establish whether there is a causal relationship among the mechanisms described by SREU and forbidden under MMEU, where an individual's beliefs drive their decisions under conditions of ambiguity (Bullock et al., 2010).

The third test is designed to expand the implications of the SREU model to other modes of decision-making by identifying violations of the MMEU model during reinforcement-learning. During reinforcement-learning paradigms (Wimmer et al., 2012; Gershman et al., 2015; Kool et al., 2022), individuals progress from a fully ambiguous state before receiving feedback to well informed decisions after many rounds of feedback (Hayden et al., 2010). Both MMEU (Gilboa and Schmeidler, 1993) and SREU (Hanany and Klibanoff, 2009) have been expanded to consider how decisions evolve in response to feedback. However, little experimental work has considered the role of ambiguity in reward learning. Under SREU, individuals use their beliefs about the distribution of probabilities as a Bayesian prior and slowly reduce the variance in that prior as they gain more feedback (Hanany and Klibanoff, 2009). This behavior reflects a relatively optimal learning scheme under uncertainty (Bayes and Price, 1763). For example, imagine you are walking down a casino hall, but are confident that you are unlikely to win a slot machine jackpot, you do not want to be swayed by seeing one person win. But in a situation where you are highly uncertain (i.e., high, and low probabilities of winning are equally likely), you should want to change your behavior quickly in the face of new information. Evidence suggesting that variance in the believed distribution of probabilities influences how people update their behavior in response to new information would falsify the extensions of MMEU to reinforcement-learning behavior (see Figure 3).

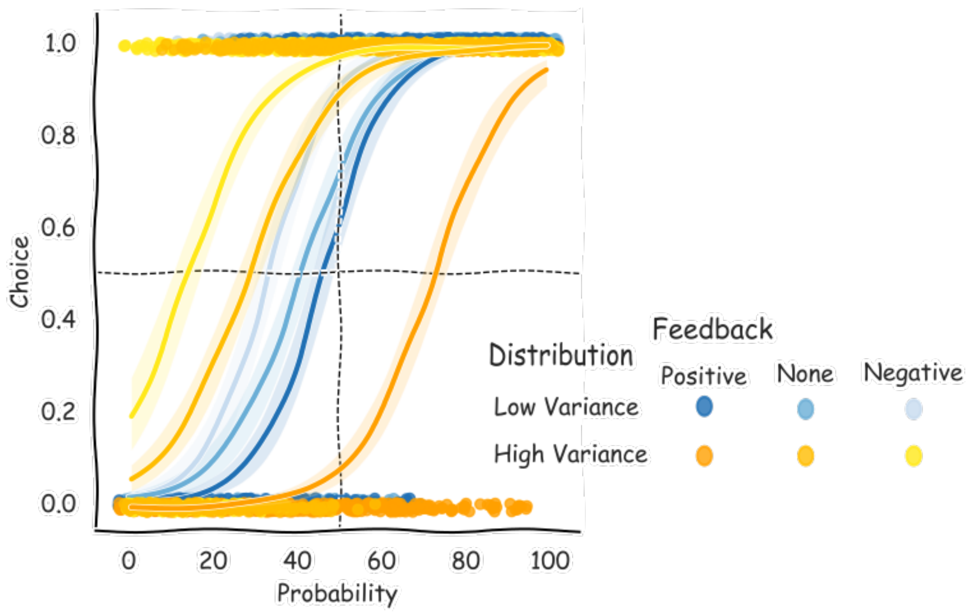

Figure 3. A simulation of ambiguity averse choices between ambiguous and risky outcomes with a given probability under SREU models after receiving feedback. Feedback on ambiguous outcomes influences choices more for ambiguous outcomes that have more variance in the distribution of probabilities. This pattern would falsify MMEU because MMEU predicts choices in response to feedback to be the same despite different distributions of probabilities.

The last test is meant to demonstrate how previous applications of the MMEU model are problematic for linking individual differences like clinical variables of interest and choice behavior. Using MMEU, ambiguity aversion has been related to several clinical disorders including addiction (Konova et al., 2020), antisocial personality disorder (Buckholtz et al., 2017), and more (Fujino et al., 2016; Pushkarskaya, et al., 2015). However, many of these relationships, between choice behavior and a clinical disorder, may be due to individual differences in beliefs about the probabilities rather than preferences. This mediation through beliefs is not compatible with MMEU and, if it exists, suggests that an alternative model which includes these beliefs, like SREU, could provide better insight for these linkages. In particular, the previously reported association between autism spectrum disorder and increased ambiguity tolerance seems likely to demonstrate just such a failure of MMEU.

One clinical disorder that was hypothesized to be related to more ambiguity aversion was autism spectrum disorder (ASD). Specifically, individuals with ASD have reported difficulties in making decisions involving uncertainty (Luke, et al., 2012) and preferences for predictability (Goris, et al., 2020) which might be related to how ambiguity is processed. However, when using MMEU autism quotient scores were shown to be associated with an increased tolerance to ambiguity (Fujino et al., 2017). Under SREU, this tolerance for ambiguity may instead be related to lower variance beliefs, which would also be consistent with two other behaviors noted in autism; slower learning in response to feedback (Goris et al., 2021, Sapey-Triomphe, et al., 2022). In particular, during probabilistic reinforcement learning tasks where participants must learn the association between particular stimuli and reward outcomes individuals with ASD exhibit poorer acquisition of less frequently reinforced stimulus reward pairs (Solomon et al., 2011) and deficits in changing behavior in response to reward contingencies opposite of those initially learned (Goris et al., 2021). This slower learning as well as ambiguity tolerant behavior would be consistent with low variance priors as detailed earlier. If the previously identified relationship between the total autism quotient and ambiguity tolerance is mediated by differences in beliefs about the probabilities (Figure 4), this relationship would demonstrate a failure of MMEU. This failure could mean that the relationship between choice and psychiatric disorders other than autism could also have been mischaracterized by MMEU or even missed when preferences and beliefs counteract each other to mirror the choices of healthy controls.

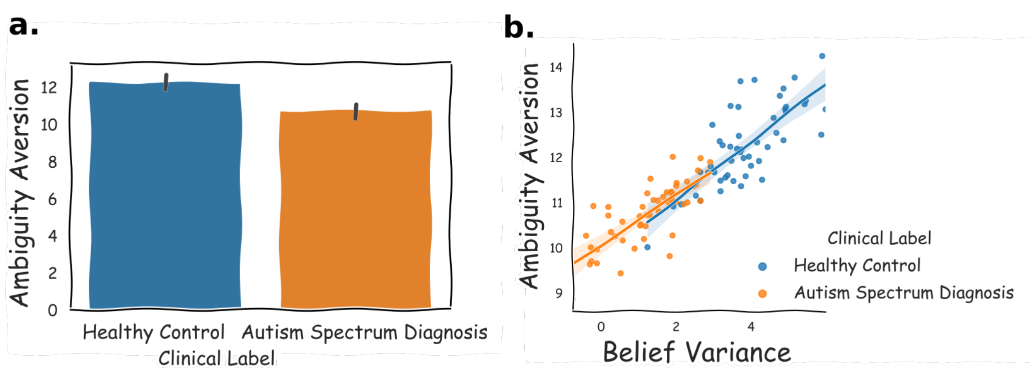

Figure 4. A simulation of a mediated relationship between autism spectrum disorder (ASD) clinical status and ambiguity averse behavior by beliefs. **(a.)** An adaptation of the ambiguity aversion effect reported in Fujino et al., 2017 using simulated data. **(b.)** Using the same data from panel “a,” the relationship between ASD and ambiguity averse choices may be driven by variance in individuals' beliefs about the distribution of probabilities.

Though the last test uses autism spectrum disorder as a vehicle to demonstrate the failure of MMEU, there is also strong clinical interest to understand how choice under ambiguity aligns with the heterogeneous nature of autism. Autism is often characterized by social communication deficits and repetitive sensory–motor behaviors (Lord, et al., 2018). However, autism is heterogeneous, and symptoms may vary significantly from individual to individual. In particular, while Fujino et al.,2017 used the autism quotient as a measure of autistic traits, the autism quotient is composed of five subscales important for understanding autism; communication, social skills, imagination, attention to detail and attention switching; (Baron-Cohen et al., 2001). These factors have also been identified using other measures including neural signatures (Lenroot, & Yeung, 2013) and are cross-cutting features of other disorders (Rodriguez-Seijas, et al., 2020) like major depressive disorder (MDD), obsessive compulsive disorder (OCD), and schizophrenia (Schwarz, et al., 2020). Though choice behavior is often related to a single measure or clinical label (Adams, et al., 2016), this evidence emphasizes the need to relate choice behavior to specific sub-constructs rather than the top-level diagnosis for autism-spectrum disorder.

In summary, it is important to understand how people make choices under ambiguity as real-life decisions rarely have known risks (Portnoy et al., 2013; Xu and Adams, 2020). However, the most common model for exploring the psychological and neurological mechanisms of decision-making under ambiguity, MMEU, may be incompatible with a key feature of human decisions (i.e., how we use our beliefs to inform our decisions). We propose four tests to identify whether human decisions under ambiguity feature an aversion to the variance in the distribution of believed probabilities, a feature that would be incompatible with MMEU but consistent with SREU (Table 1). The first two tests are meant to find experimental evidence that ambiguity aversion is driven by the believed variance in the distribution of probabilities, falsifying MMEU. The second two tests are meant to demonstrate wider implications by linking beliefs about the distribution of probabilities to another decision context (i.e., reinforcement learning) as well as a clinical variable of interest (i.e., the autism quotient). Lastly, we take an additional step to identify the subcomponents of autism which may be related to choice behavior under ambiguity. Positive indications for any of these tests would be incompatible with MMEU and suggest that experiments that have relied on this model are missing a key feature of ambiguity and should be revisited.

Table 1. A table describing each of the four tests and predictions under MMEU and SREU.

Test	MMEU Prediction	SREU Prediction
1. Aversion to Variance in Probability: Direct Experience	Only the stated **range of probabilities and not variance of probability will affect choices** under ambiguity.	The **believed variance of probability will affect choices** under ambiguity. Stated range will have no effect after controlling for how range effects variance.
2. Aversion to Variance in Probability: Normalized Experiences	The order of exposure to variance in probability **will not affect choices** under ambiguity.	The order of exposure to variance in probability **will affect choices** under ambiguity through perceived variance.
3. Faster learning under higher variance distributions.	**Changes in choice** behavior in response to feedback **are the same** for high and low variance probability distributions	**Changes in choice** behavior in response to feedback are **greater for high variance** compared to low variance distributions.
4. Individual Differences: Autism Quotient	Differences in ambiguity averse choices are **only driven by differences of preference** for ambiguity.	Differences in ambiguity averse choices driven by differences of preference for ambiguity and **beliefs about the probabilities.**

CHAPTER 2:
AIMS AND HYPOTHESES

Subjective recursive expected utility (SREU) and maxmin expected utility (MMEU) models have both been suggested as ways to describe human decisions under ambiguity. One key difference between the models is that SREU allows for decision makers to have unique subjective beliefs about the underlying probabilities for different ambiguous stimuli which influence their decisions. Problematically, previous experiments exploring this idea have used explicit descriptions of the distribution of probabilities (Halevy et al., 2009), but ambiguity is meant to reflect a lack of this explicit information.

To address this problem, we collected data in a pilot study (N=53) which was a part of a larger study being conducted at Temple University Brain Imaging center. This pilot was used to test an implicit manipulation of individual beliefs about the distributions of probabilities. In the pilot, participants learned about the distributions in a prior “risky” decision-making phase and made choices related to those distributions in an “ambiguous” decision phase. We showed that during the ambiguous decision phase individuals were more averse to lotteries associated with a greater variance in probabilities experienced during the risky decision phase. While replicating previous results (Halevy, 2007), our use of an implicit rather than explicit manipulation showed SREU can predict behavior beyond MMEU under a condition of true ambiguity. We also found evidence that the autism-quotient scale was associated with reduced variance in reported beliefs about the distribution of probabilities, possibly suggesting that individual differences in beliefs was responsible for the relationship identified in Fujino et al., 2017. Combined, this evidence suggests that human choices under ambiguity may be inconsistent with axioms of MMEU and should be further explored using implicit manipulations of the beliefs about the distribution of probability.

The purpose of the current study is to identify whether beliefs about the likely probability are a key feature of decisions under ambiguity, as well as early stages of feedback learning as ambiguity resolves, and lastly a key feature of individual differences in decision-making as it relates to a clinical variable of interest, the autism-quotient.

2.1 Specific Aim 1: Determine whether beliefs about likely probabilities drive ambiguity aversion.

Under MMEU beliefs about the underlying distributions of probabilities are not allowed to influence decisions under ambiguity, evidence showing a causal relationship between these beliefs and decisions would falsify the MMEU model. In this aim we look at two experimental manipulations (See Chapter 3 for more description) meant to shape individual beliefs about the distribution of probabilities through direct experience and using the order of experiences.

Hypothesis 1a: During the ambiguous decision task, participants will be more averse to ambiguous lotteries which were associated with a high compared to low variance in the probabilities, learned during a prior risky decision task.

Hypothesis1b: During the ambiguous decision task, participants will be more averse to high variance lotteries if, during the risky decision task they learned about the high variance distribution after the low variance distribution.

Hypothesis 1c: The relationship between both experimental manipulations, using direct experience and order of stimuli, and aversion to lotteries with high variance in probability will be partially mediated by the variance of each participant's reported memory of the distribution of probabilities.

If these hypotheses are correct, it would show that individuals use their experiences during situations where they know the risks to inform their decisions in situations where the risks are unknown. This would falsify MMEU where only the range of probabilities affects ambiguity aversion.

2.2 Specific Aim 2: Examine associations between beliefs about likely-probabilities and feedback learning.

Both the SREU and MMEU model have been extended to better understand how ambiguity resolves through feedback learning. However, SREU suggests that individual beliefs about the probabilities can influence reinforcement learning schemes as a Bayesian prior. The following two hypotheses are meant to identify whether these beliefs influence feedback learning.

Hypothesis 2a: Participants will be slower to change their decisions in response to feedback for ambiguous stimuli associated with a lower variance in probability.

Hypothesis 2b: Changes in decisions will be related to an interaction of the estimated mean and variance of the distribution of probabilities for an optimal Bayesian learner given each participant's reported belief about the probabilities as a prior.

Support for these hypotheses would demonstrate the utility of SREU in other domains of decisions and motivate further extensions of the model.

2.3 Specific Aim 3: Demonstrate the role for beliefs in linking choice behavior and autistic traits.

Maxmin expected utility has been applied to link choices under ambiguity with a wide variety of clinical disorders. However, due to the inability of MMEU to incorporate beliefs into these decisions, these relationships may be mischaracterized. One previous study used MMEU to link autism-spectrum disorder with more ambiguity tolerant decisions (Fujino et al., 2017). However, some evidence suggests individuals with autism may also have low variance beliefs which could drive less ambiguity averse decisions under SREU despite similar or more averse preferences. Under MMEU, individual differences in choice are only driven by different preferences. Therefore, if individual variance in beliefs about the probabilities mediates the relationship between autism and individual differences in choices under ambiguity, it would demonstrate a failure of MMEU. We address this aim by testing three hypotheses.

Hypothesis 3a: Autistic traits measured by the autism quotient, will be negatively correlated ambiguity aversion.

Hypothesis 3b: Autistic traits will be negatively correlated with the variance of individuals' reported belief about the distribution of probabilities.

Hypothesis 3c: Variance of an individual's reported belief about the probabilities mediates the relationship between autistic traits and ambiguity aversion.

While these hypotheses are specific to autism spectrum disorders, evidence for these hypotheses could suggest that any disorder or individual difference which has been analyzed using MMEU has been mischaracterized. Additionally, these hypotheses focus on the total autism quotient score as that is what was reported by Fujino et al., 2017. However, we recognize that autistic traits are multi-faceted (Baren-Cohen et al., 2001) and we will perform exploratory analyses to identify any relationships between the subscales of the autism quotient, the believed distribution of probabilities, and ambiguous choice. This may help to identify clinical features that cut through different psychiatric disorders related to preferences under ambiguity (see section 4.4.6).

CHAPTER 3:
METHODS

The data for this project was collected using an experiment performed online. Each participant performed a linked pair of colored lottery tasks (described in section 3.2) followed by two self-report measures including the Autism Spectrum Quotient and a memory questionnaire about the risky lottery task (described in section 3.3).

3.1 Power analysis and recruitment

Our target sample for this study of 250 participants was determined after conducting an apriori power analysis of between- and within-subjects effects. Power analyses used conservative effect-size estimates from those observed in our pilot data (N=53). To maintain a conservative estimate, we used the smallest observed within and between effects of interest from the pilot study and translated the effects into Cohen's d. The within-subjects effect was estimated from the effect of the different distributions in the risky lottery task on decisions in the hidden lottery task ($t(52) = -2.344$, $p=0.019$, $d=.69$). The between-subjects effect was determined from the correlation between the Imagination subscale of the AQ, as this was the smallest correlation, ($r(38) = 0.35$, $p=0.02$), which translated into an effect size of Cohen's d=0.75 (Ruscio, 2008). To further maintain a conservative estimate of the effect, we calculated a 95% confidence interval for each effect (Fitts, 2020) and took the lower bound as the estimate. Using this approach, we determined the effect sizes to be $d^* = 0.29$ for between subjects and d*= 0.4 for within-subjects analyses. Power analyses used α = .05 and power = .80 for both tests and our conservative effect sizes suggested a minimum sample size of N=97 to detect within subject effects and N=187 to detect between subjects. Thus, our target sample size of N = 250 is sufficiently large to identify the hypothesized effects.

To accommodate collection of these samples, we used the online experiment platform Cognition.Run (https://www.cognition.run/) to host the experiment and collect data. To recruit a large and representative sample we used another online service called Prolific. The Prolific service also allowed us to compensate participants for their involvement ($6 for their time) and link outcomes from one of their choices to a bonus they received after finishing the experiment (either $0, $3, or $7).

3.2 Participants

A total of 298 participants [154 females; age: mean (M) = 45.4 years, (SD) = 15.6 years] completed the experiment. Participants were prescreened to through Prolific so that the sample matched recent data from the 2022 U.S. Census on demographics of age, sex, and ethnicities. Participants gave written informed consent as part of a protocol approved by the Institutional Review Board of Temple University. Additional exclusion criteria were applied as described in the analysis plan (section 4.1). For more detailed demographic information including race, sex, and education see table 2.

Table 2. Demographic information about the sample. The size of the sample and percent of the is listed for each uniquely indicated sex, race, and level of education.

	N	%
Sex		
Female	154	52%
Male	143	48%
Other	1	<1%
Race		
White or Caucasian	207	73%
Black or African American	32	11%
Hispanic	15	5%
Asian or Pacific Islander	21	7%
Native American or Alaskan	1	<1%
Multiple or Other	8	3%
Education		
Some High school No Diploma	4	1%
High School or Equivalent	40	14%
Some College No Degree	60	21%
Associates Degree	31	11%
Bachelor’s Degree	99	34%
Master’s Degree	42	15%
Doctoral Degree	8	3%

3.3 Linked Colored Lottery Tasks

To implicitly manipulate individual beliefs about the probabilities, we used a linked set of tasks including a Risky Colored Lottery task (3.2.1) and Hidden Colored Lottery task (3.2.2). In the Risky Colored Lottery task, participants learned about the unique distribution of probabilities for each color of lottery as they make decisions between a known risk and safe amount of money. In the hidden colored lottery task, the exact probability is hidden from participants, but they are shown the color of the lottery allowing the participant to make decisions based on the unique distribution of probabilities learned in the Risky Colored Lottery task.

3.3.1 Risky Colored Lottery Task

Participants completed a series of two-alternative forced-choice lotteries, where they chose between a risky lottery and a safe amount of money. The risky lotteries represent a chance to win either a prize of money or $0. The lotteries are presented as a pie chart with a ring around it. The prize money is displayed at the top and the probability of winning the prize at the bottom of the chart (See figure 5). Additionally, the probability of winning the prize money is shown as the bright region of the pie chart while the dark region represents the probability of winning $0. Throughout the task the chance to win the lottery changed but the prize money stayed at $7, and the safe amount of money stayed at $3.

The task used three colors of lotteries (red, blue, and green) and participants made 20 choices with one color of lottery before moving onto the next. Importantly, each color was randomly assigned to one of three different distributions of probabilities, either wide, narrow, or skewed appearing in one of four random orders (narrow, wide, skew; wide, narrow, skew; narrow, skew, wide; skew, narrow, wide). During the risky decision task, the color assigned to the wide distribution appears with probabilities of winning near the extremes (0% and 100%) decreasing in frequency as probabilities get closer to 50% (see figure 5). The color assigned to the narrow distribution appears with lotteries most often with a 50% chance of winning and decrease in frequency for probabilities furthest from 50%. The color assigned to the skewed distribution appears most often with a 70% chance of winning and decrease in frequency for probabilities furthest from 70%.

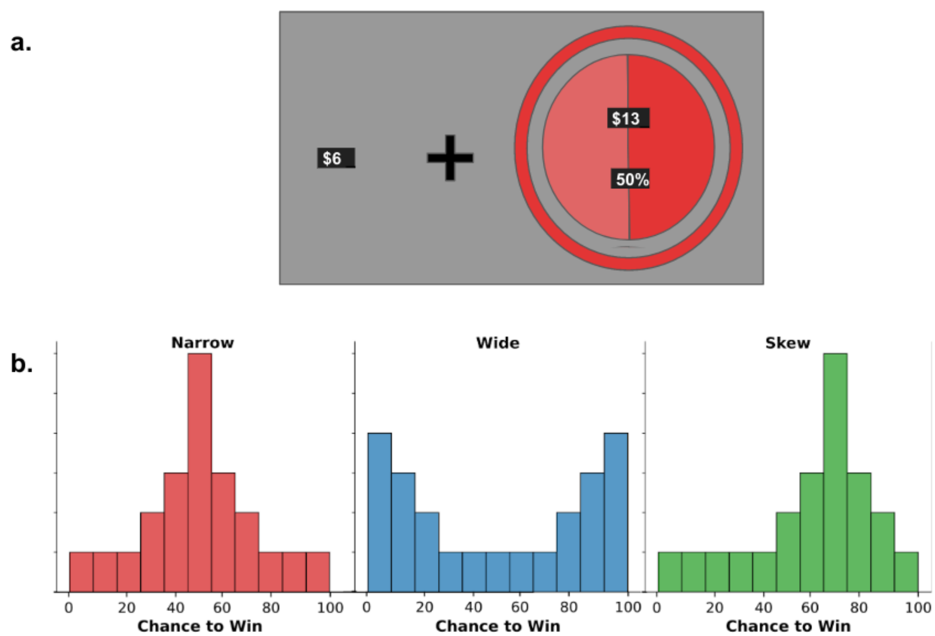

Figure 5. A schematic of the risky decision task design. **(a.)** A visual representation of the two-alternative forced choice. Lotteries were randomly presented on either the left or right side of

the screen. **(b.)** Three histograms representing how often color lotteries assigned a narrow, wide, and skewed distribution were presented with a particular chance of winning the prize of $7.

3.3.2 Hidden Colored Lottery Task.

Participants completed a series of two-alternative forced-choice lotteries, where they can choose between a risky lottery and a “hidden” lottery. The hidden lottery appears as a pie chart from the previous risky decision task with the pie chart either fully or partially occluded and the range of possible chances of winnings listed instead of a known probability. Importantly however, the color of the lottery was not occluded, allowing participants to infer how often a lottery would have previously appeared with a particular probability of winning.

Participants made 15 choices between the hidden lotteries and one where the chance of winning is known. Both lotteries have the same prize but the probability of winning the known lottery changes as participants make their decisions. A stair-casing procedure was used to determine the probability of winning the risky lottery such that it starts with a 50% chance of winning decreasing by 10% if the participant chooses the risky lottery and increasing by 10% if the participant chooses the ambiguous lottery. When a participant switches between choosing the risky and ambiguous lottery 2 times the step size is cut in half (e.g., 10% to 5%) and increased by a half (e.g., 10% to 15%) if the participant makes the same choice 2 times in a row. These probabilities were bound between 100% and 0%.

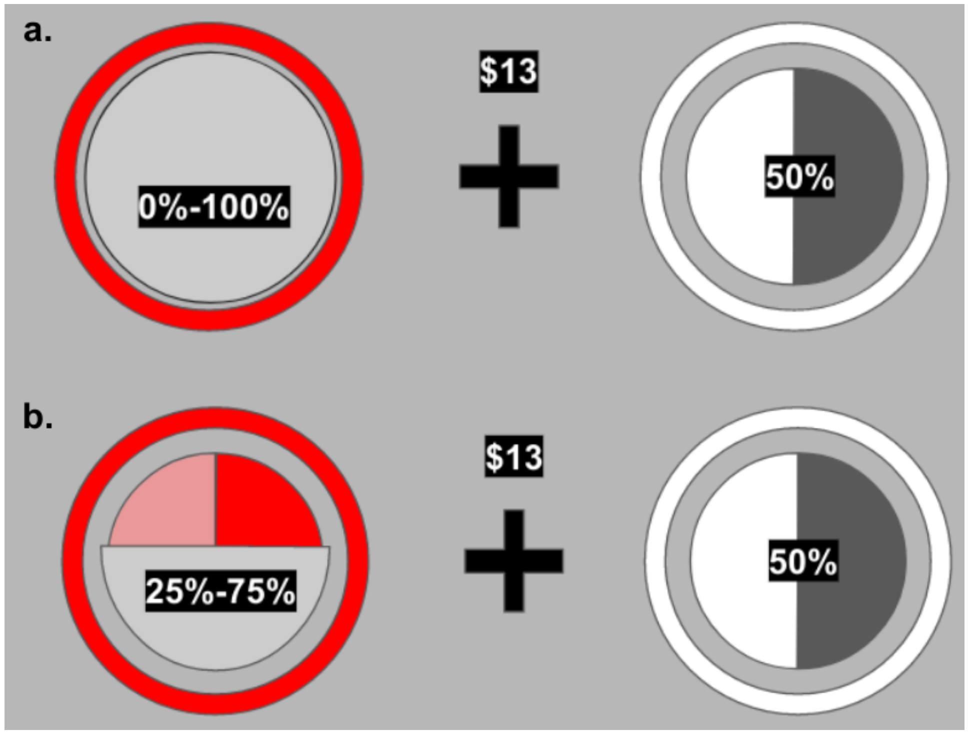

Figure 6. A schematic of the two-alternative forced choice for the hidden lottery task. Each choice presents a risky lottery and hidden lottery randomly presented on the left or right. Like previous studies exploring ambiguity (Levy et al., 2012) the probability of winning is obscured either completely (a.) or partially (b.). However, the color of the ring around the lottery and portions of lottery that are un-obscured indicate whether the distribution the lottery is from (e.g., narrow, wide, or skewed).

3.3.3 Hidden Colored Lottery Task With Feedback

Participants also played a version of the hidden lottery task with feedback. In this task participants have a sampling period where they play the hidden lottery before making their decisions as described in the Hidden Colored Lottery Task (section 3.3.2). Participants play the lottery by pressing the space bar and are shown a screen with a gold coin and the words “You won!” or a grey coin with the words “You didn’t win” to indicate whether they did or did not win that “play” of the lottery. Again, the color of the lottery (red, green, or blue) is displayed so that participants can include this information in combination with the feedback they receive.

3.4 Questionnaires

After completing the linked colored lottery tasks participants were asked to complete two questionnaires; the Autism-Spectrum quotient scale and a memory questionnaire that asked about participants' experience during the experiment.

3.4.1 The Autism-Spectrum Quotient (AQ)

Participants completed Baren-Cohen's Autism-Spectrum Quotient (2001), which is a widely used self-report questionnaire commonly used to assess autistic-like traits and behaviors expressed by neurotypical individuals. The measure consists of 50 Likert items (1=strongly disagree, 4=strongly agree). The AQ scale has 5 factors including social skills, attention switching, attention to detail, communication, and imagination. The total AQ score has been previously reported with acceptable internal consistency (a = .79-.82) (Stevenson and Hart, 2017; Austin, 2005), moderate internal consistency for subscales (a=.63-.77) (Baren-Cohen et al., 2001), as well as 2-week test-retest reliability for the total score (r=.86) (Stevenson and Hart, 2017).

3.4.2 Memory Questionnaire

Participants also completed a memory questionnaire meant to assess how well they learned the second order distributions of each of the color lotteries while making decisions in the risky decision task. For each color lottery the participants are asked to recall how often they encountered a lottery that had a 0-100% chance of winning in steps of ten (i.e., 0%, 10%, 20% etc.). In the pilot study, participants' reports did an excellent job reflecting the manipulation with participants correctly reporting the lotteries associated with the greatest mean chance of winning (t (45) =12.5 $p<0.00001$, $d=3.7$) and variance in chance of winning (t (45) =6.8 $p<0.00001$. $d=2.02$).

CHAPTER 4:
ANALYSIS PLAN

Computational models like MMEU and SREU are often holistically tested through a process of fitting, parameter extraction, and model comparison to identify which best describes the given behavior (Wilson and Collins, 2019). However, rather than considering differences overall performance, we can look for evidence choice behavior violates the axioms of MMEU by seeing if choices under ambiguity are sensitive to individuals' beliefs about the distribution of probabilities (see Table 1) and directly falsify this model (Popper, 1959). Identifying a significant influence of beliefs about the distribution of probabilities does not need computational modeling and can be performed with typical frequentist methods including logistic regression, mediation, and correlation analyses. We have additionally made the code available that we used to run the described analyses and make the included figures (www.github.com/jbdenniso/LimitInfo).

4.1 Outliers and Exclusions

Due to common concerns of data quality related to online collection (Brühlmann et al., 2020) we used two exclusion criteria to ensure participants understood and engaged with the task.

First, we excluded participants from all analyses who reported zero variance distributions in the memory questionnaire (section 3.3) as this suggested individual either were not paying attention during the risky decision task or did not understand the question. A total of 18 participants were excluded from analyses for reporting at least one zero variance distribution.

Second, we excluded participants who did not understand or were not paying attention during the ambiguous choice or reinforcement learning task. Here we deviate from our initial plans to identify participants who did not choose the risky lottery more often as the chance of winning increased using logistic regression. These analyses ran into convergence issues especially for participants with linearly separable and missing data. After a quick visual inspection of our data, we adopted a simpler rule, excluding participants who chose a safe $3 over a 100% chance at $7 or chose a 0% chance at $7 over a safe $3, as this behavior would not be consistent with any logical decision rule. In the ambiguity task, 13 participants were excluded and in the reinforcement learning task 18 were excluded due to these choice checks. This left 267 participants for the ambiguity task and 262 for the reinforcement learning task available for analysis. Lastly, our analyses were reperformed but including participants who were excluded by these criteria.

4.2 Testing Hypotheses: Specific Aim 1

Hypothesis 1a: During the ambiguous decision task, participants will be more averse to ambiguous lotteries which were associated with a high compared to low variance in the probabilities, learned during a prior risky decision task.

Hypothesis1b: During the ambiguous decision task, participants will be more averse to high variance lotteries if, during the risky decision task they learned about the high variance distribution after the low variance distribution.

Hypothesis 1c: The relationship between both experimental manipulations, using direct experience and order of stimuli, and aversion to lotteries with high variance in probability will be partially mediated by the believed variance of reported in participants' memory of the distribution of probabilities.

4.2.1 A Description of Variables for Hypotheses 1a and 1b

Choice: A binary value representing whether participants chose the hidden or risky lottery on a particular trial of the hidden lottery task

Probability: A ratio value representing the probability of winning the risky lottery in the ambiguous choice task (see section 3.4)

Distribution: A categorical variable representing the distribution of probabilities associated with the color of a hidden lottery (e.g., wide, narrow, skewed) (see section 3.2.1)

Order: A categorical variable representing whether, during the risky decision task, individuals experienced the color lottery associated with a wide distribution before or after the narrow distribution.

Equivalence point: The probability of winning a risky lottery equally likely to be chosen by a participant as a hidden lottery. This is determined by fitting a logistic regression for each condition. **Choice ~ Intercept + Probability** and dividing the resulting coefficient for the intercept by the coefficient related to the probability.

4.2.2 Statistical Technique

To test whether the distributions experienced during the risky lottery task influenced choices during the hidden lottery task, we use a hierarchical logistic regression.

Choice ~ Probability + distribution [‘wide’, ‘narrow’] + (1|sub)

To test whether the order of distributions in the risky lottery task influenced choices during the hidden lottery task, we use a logistic regression on two sets of data. We fit the following regression using trials in the hidden lottery task associated with the wide distribution.

Choice ~ Probability + Order [wide before or after narrow]

If either the distribution or order of distribution is unable to show a significant effect in the predicted direction, we will conduct a check of each manipulation on the reported variance in individuals’ beliefs using the appropriate (within vs between subjects) t-test.

Lastly, we check whether the relationship between experimental manipulations and participants’ choices are mediated through the reported variance in their beliefs about the distribution of probabilities. A significant indirect effect would indicate that the relationship between our manipulations and individual choices are driven by the effect of the manipulation on individual’s beliefs and falsify MMEU.

4.3 Testing Hypotheses: Specific Aim 2

Hypothesis 2a: Participants will be slower to change their decisions in response to feedback for ambiguous stimuli associated with a lower variance in the distribution of probability.

Hypothesis 2b: Changes in decisions will be related to an interaction of the estimated mean and variance of the distribution of probabilities for an optimal Bayesian learner given each participant's reported belief about the distribution of probabilities as a prior.

4.3.1 A Description of Variables for Hypotheses 2a and 2b

Choice: Participant's binary choice of the risky or hidden lottery during the hidden lottery task with feedback (section 3.2.2)

Probability: A ratio value representing the probability of winning the risky lottery

Distribution: A categorical variable representing the distribution of probabilities associate with a color of hidden lottery (e.g., wide, narrow, skewed)

Feedback: A ratio variable representing the percent of trials with rewarding feedback during the feedback version of the hidden lottery task

Mean(posterior): This will be calculated by taking a weighted average from the distribution given by applying Bayes rule to each participant's report of their believed distribution.

(P (feedback | Chance of winning) * P (Chance of winning)) /P(feedback).

Var(posterior): This will be calculated by taking a weighted variance from the distribution given by applying Bayes rule to each participant's report of their believed distribution.

(P (feedback | Chance of winning) * P (Chance of winning))/P(feedback)

4.3.2 Statistical Technique:

We use hierarchical logistic regression to test the following models.

H2a.) Choice ~ Probability * Distribution ['narrow', 'wide'] * Feedback+ (1|sub)

A significant interaction of distribution and feedback on choice could suggest that individuals are faster at updating their behavior under ambiguity when applying feedback to large variance distributions.

H2b.) Choice ~ Probability + Mean(posterior) * Var (posterior) + (1|sub)

A significant effect of Mean(posterior) and Var(posterior) or an interaction suggests that individual choices given feedback reflect the posterior belief of an optimal Bayesian learner.

Evidence for either of these hypotheses would suggest that beliefs are important aspects of understanding how ambiguity resolves in reinforcement learning paradigms and falsify extensions of MMEU.

4.4 Testing Hypotheses: Specific Aim 3

Hypothesis 3a: Autistic traits measured by the autism quotient, will be negatively correlated ambiguity aversion.

Hypothesis 3b: Autistic traits will be negatively correlated with the variance of individual's reported belief about the distribution of probabilities.

Hypothesis 3c: Variance of an individual's reported belief about the probabilities mediates the relationship between autistic traits and ambiguity aversion.

4.4.1 A Description of the Variables for Hypotheses 3a, 3b, 3c

Choice: Individual's binary choice of the risky or ambiguous lottery during

Probability: A ratio value representing the probability of winning the risky lottery during a trial of the hidden lottery task.

Distribution: A categorical variable representing whether the distribution of probabilities from the risky colored lottery task (wide, narrow, skewed)

Var(distribution): The average variance in the chance individuals self-reported memory in frequency in the probability of winning across all presented lotteries

Mean(distribution): The average mean of the chance individuals self-reported memory in frequency in the probability of winning across all presented lotteries

Equivalence point: The probability of a risky lottery where individuals are equally likely to choose a risky or ambiguous lottery. This is determined by fitting a logistic regression for each condition. **Choice ~ Intercept + Probability and** dividing the resulting coefficient for the intercept by the coefficient related to the probability.

Autistic traits: The total score from the autism-quotient scale is used with follow up tests using appropriate subscales (Social, Communication, Imagination, Attention to detail, Attention Switching).

4.4.6 Statistical Technique

To replicate the results from Fujino et al., 2017 without fitting a formal maxmin model, we run a mixed effects logistic regression. This is done for each distribution to determine whether smaller autism-quotient scores are associated with more ambiguity averse choices during the hidden lottery task.

H3a.) Choice ~ Probability + Autistic Trait

To test for a relationship between AQ scores and the variance in the reported beliefs, we conduct a correlation between the total AQ score and the mean variance for all reported distributions.

Lastly, we use a mediation analysis to test whether reported variance in beliefs about the likely probabilities mediates the relationship between Autistic traits and equivalence points.

Our initial hypotheses focus on the total autism quotient score to determine whether already reported results using MMEU and the total autism quotient are mediated by factors undetectable by MMEU (Fujino et al., 2017). However, we recognize criticisms that the relationship between autistic traits, beliefs about the probabilities, and choices under ambiguity may be driven by a subcomponent of the autism quotient. Therefore, we also planned exploratory analyses on the five subcomponents; communication, social skills, imagination, attention to detail and attention switching; by carrying out the same analyses as the total score and correcting for multiple comparisons using a family-wise error rate. This can help to establish which subscales converge or diverge from individual beliefs about the probabilities and preferences for different amount of variance in the probabilities.

CHAPTER 5:
RESULTS

Our project contains three sets of apriori hypotheses to assess whether individual beliefs about the distribution of probabilities are incorporated into choices under conditions of ambiguity. The first set of hypotheses tests the effects of two manipulations of the believed variance in distributions on choice and whether individual reports of believed variance mediate the effects the manipulations have on choice. The second set includes two hypotheses test how believed variance in distribution of probabilities interacts with feedback to influence future choices. Lastly, the third set of hypotheses tests whether individual differences in how people construct beliefs about the distribution of probabilities effects the relationship between a clinical variable of interest, the autism quotient, and choices under ambiguity.

5.1 Perceived Variance in Probabilities Increased Preference for Ambiguity

As indicated in the analysis plan, we conducted a manipulation check to ensure that experienced and order of distribution affected reported beliefs about the distribution. As expected, participants reported distributions had greater standard deviation in the wide as compared to narrow distributions ($t(279) = -14.96$, $p<0.0001$). We additionally hypothesized that participants who made decisions about the narrow distribution before the wide distribution would normalize the probabilities (Louie et al., 2013) and report greater variance in the wide distribution. Indeed, we found that reports of the wide distribution showed greater variance when given by participants who experienced the narrow distribution first ($t(278) = -2.38$, $p=0.019$). This indicates that both manipulations worked as planned.

As an additional check on the accuracy of these ratings we conducted two correlations, finding a significant relationship between the means that individuals reported for each distribution and the true mean ($r=0.40$, $p<0.001$) as well as the standard deviation that individuals reported for each distribution and the true standard deviation of those distributions ($r=.58$, $p<0.001$). However, we also found that individuals significantly underestimated the means of the narrow ($t=-2.61$, $p=0.009$) and skewed distribution ($t= -20.85$, $p<0.001$). Additionally, participants tended to overestimate the standard deviation of the narrow ($t=14.93$, $p<0.001$) and skew ($t= 17.14$, $p<0.001$) and underestimated the variance of the wide distribution ($t= -25.81$, $p<0.001$)

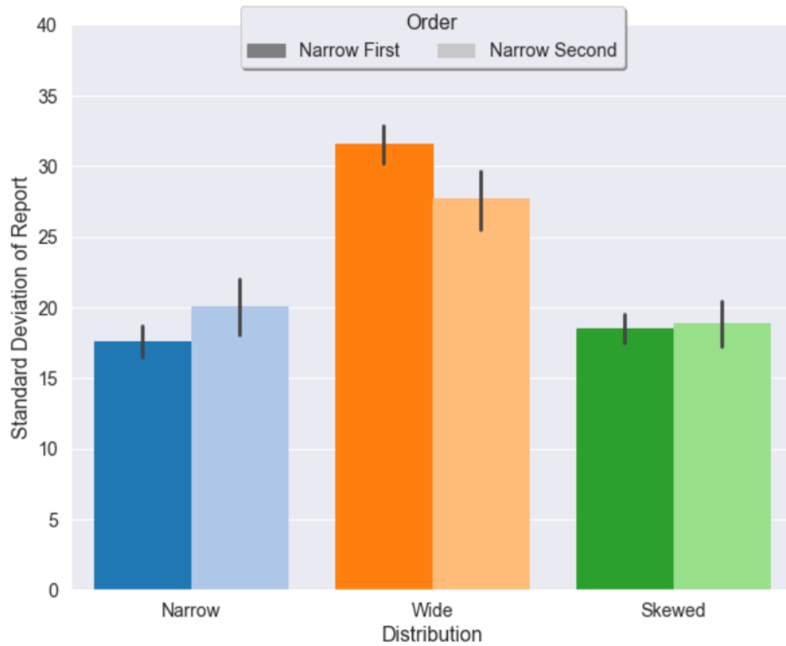

Figure 7. Participants reports showed that they remembered seeing greater variability in the chance of winning for the color lottery associated with the wide condition as compared to the Narrow and Skewed conditions. Participants who experienced the narrow before the wide condition reported greater variability in the chance of winning for the wide distribution.

We first evaluated if participants would be more averse to ambiguous lotteries associated with wide (high variance) as compared to narrow (low variance) distributions using a hierarchical logistic regression (see table 3). Our regression included participant's choices during the ambiguous choice task as the dependent variable (hidden vs risky lottery) and the probability of winning the risky lottery as well as the distribution associated with the hidden lottery (wide vs narrow) as the independent variables. Results of our analysis showed that probability of winning the risky lottery significantly increased the chances of choosing the risky lottery (OR= 1.8+e08, 95%CI=[2.79e+07,1.60+e08]). While we hypothesized that participants would be averse to the wide distribution, our results suggested that making choices about the wide distribution significantly decreased the chance of choosing the risky lottery over the hidden lottery (OR= 1.11, 95%CI= [0.788 ,1.5]) (Figure 8). Although this evidence suggests that we were wrong about the direction of the effect, the association of the hidden lottery with different variance in distributions still significantly influenced participant's choices under ambiguity demonstrating that individuals do incorporate this information to make decisions under ambiguity and violating the assumptions of MMEU.

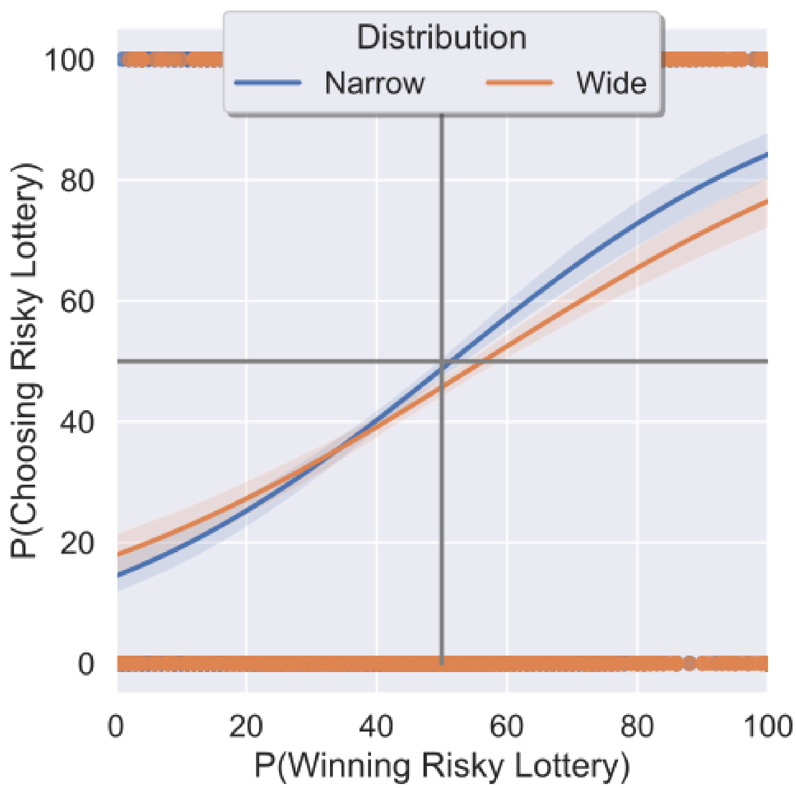

Figure 8. Logistic regression for the effect of the probability on winning the risky lottery on choosing the risky over the hidden lottery drawn separate for each distribution. The grey lines represent the optimal switching point for an ambiguity neutral decision maker. Regression lines which cross the horizontal line to the left of the vertical are ambiguity averse while those crossing to the right are ambiguity seeking.

Table 3. Results of the hierarchical logistic regression for the effect of distribution on choice.

	B (SE)	95% CI OR Lower	OR	95% CI OR Upper	p
Intercept	-4.148 (0.180)	0.011	0.016	0.022	<0.001
P(Win)	8.732 (0.362)	3050.390	6199.964	12601.524	<0.001
Distribution	-0.276 (0.050)	0.688	0.759	0.836	<0.001

We also used a logistic regression to test the effects of order on choice, the results of which are reported in table 4. Here, however, while we found a significant overall model ($\chi2= 317.55$, $p<0.001$), indicating good model fit, and effect of probability (OR= 2.43×10^8, 95%CI= [2.52 x 107, 2.48 x 1010], $p<0.001$) we saw no effects of order on choice ($p>0.05$). This suggests the effect of order presentation in the risky decision phase on variance in probability did not translate to an observable effect on choice behavior.

Table 4. Results of the hierarchical logistic regression for the effect of order on choice.

	B (SE)	95% CI OR Lower	OR	95% CI OR Upper	p
Intercept	-10.395 (0.666)	<0.001	<0.001	<0.001	<0.001
P(Win)	21.630 (1.184)	2.52×10^7	2.43×10^8	2.48×10^{10}	<0.001
Order	-0.360 (0.434)	0.298	0.698	1.635	0.411

Lastly, we aimed to identify if individual beliefs were the mechanism that influenced the causal relationship between our experimental manipulations and choice. To accomplish this aim we conducted two mediation analyses following the Hayes procedure (Hayes and Rockwood, 2017). In the first mediation model, we entered the distribution (wide or narrow) as the predictor variable, the variance of an individual's reported distribution for the distribution as the mediator, and their equivalence point as the outcome variable. The equivalence point represents the theoretical probability of winning a risky lottery for which a participant is equally likely to choose the hidden and risky lottery (see section 4.2.1 for details on how this was obtained). The indirect effect of distribution on choice through variance in beliefs as a mediator was found to be statistically significant (B (SE) = 0.018 (0.009), 95% C.I. [9×10^{-4}, 3.4×10^{-2}], p=0.036). This finding suggests that the manipulation of individual beliefs affects choices under ambiguity and that the individual influence it had on those beliefs was the mechanism through which the manipulation affected choices.

The second model again used the variance of an individual's reported distribution for the distribution as the mediator, and their equivalence point as the outcome variable, but instead used the order manipulation (Before or After) as the predictor variable. This time a significant path was shown from order to variance in belief (B (SE) = 3.8 (1.34), 95% C.I. [1.19, 6.47], p = 0.005) and variance in belief to equivalence point (B (SE) = -0.002 (0.001), 95% C.I. [-0.004, -0.0002], p=0.032) but there was no significant direct (p=0.6) or indirect effect (p=0.056). This suggests that though the manipulation affected the variance in participants' beliefs, it did not influence their choices through this mechanism.

5.2 Perceived Variance in Probabilities Moderates Reinforcement Learning Behavior.

Both the SREU and MMEU model have been extended to better understand how ambiguity resolves through feedback learning. However, SREU suggests that individual beliefs about the probabilities can influence reinforcement learning schemes as a Bayesian prior. In particular, beliefs with greater variance should be more susceptible to positive and negative feedback (Bayes and Price, 1763). To test whether participants changed their decisions more in response to feedback for the hidden lotteries associated with greater variance in probabilities we used a hierarchical logistic regression. The resulting overall model was found to be significant, X2 (6, N = 245) = 975.103, $p < 0.001$, suggesting a goodness of fit. The results for all main effects and interactions are reported in table 5, but importantly we saw a significant interaction between the distribution and feedback (OR=0.484, 97.5%CI= [0.268, 0.875], p=0.016) which suggested that individuals became less likely to choose the risky over hidden lottery after winning a lottery in the wide condition than in the narrow condition. This interaction implies that, as hypothesized, beliefs with greater variance in the distribution of probability influence individuals to make greater changes to their choices in the early stages of reinforcement learning as ambiguity resolves.

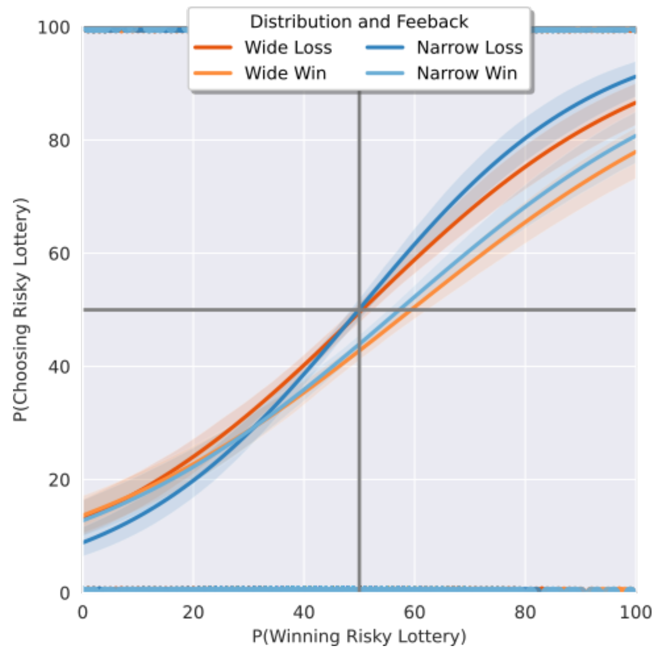

Figure 9. Logistic regression for the interaction between distribution and feedback on choices of the risk over hidden lottery. The grey lines represent the optimal switching point for an ambiguity neutral decision maker. Regression lines which cross the horizontal line to the left of the vertical are ambiguity averse while those crossing to the right are ambiguity seeking.

Table 5. Results of the hierarchical logistic regression for the effect of distribution and feedback on choice.

	B (SE)	95% CI Lower	OR	Upper	p
Intercept	-5.068 (0.203)	0.004	0.004	0.009	<0.001
P(win)	10.695 (0.413)	1.96×10^4	4.4×10^4	9.9×10^4	<0.001
Distribution	0.687 (0.213)	1.309	1.988	3.020	0.001
Feedback	0.378 (0.220)	0.947	1.459	2.247	0.086
P(win) * Distribution	-1.521 (0.452)	0.090	0.218	0.530	0.001

Table 5 continued

P(win) * Feedback	-1.791 (0.453)	0.069	0.167	0.405	<0.001
Distribution * Feedback	-0.725 (0.302)	0.268	0.484	0.875	0.016
P(win) * Distribution * Feedback	1.339 (0.611)	1.151	3.816	12.650	0.028

The interaction between distribution and feedback from the previous result implied that individuals may have been updating their beliefs and resulting choices for greater variance distributions, like a Bayesian learner. However, our second hypothesis tests this idea more explicitly by entering the mean and variance of an optimal posterior belief into our logistic regression, obtained for each participant by applying Bayes Rule (see section 4.3). To estimate this belief, we used individual reports of the distribution as the prior, the probability of the outcome (winning or not winning) as the likelihood, and the overall chance of the outcome based on the prior as the marginal probability. We were then able to take the mean and standard deviation of the newly calculated posterior and enter it into a hierarchical logistic regression along with the probability of winning the risky lottery to predict choices between the risky and hidden lottery (Results in table 6). Results indicated that larger means in the estimated posterior decreased the chances of choosing the risky over the ambiguous lottery (OR= 0.98, 97.5% CI = [0.97, 0.99], p<0.001) but not the variance in the posterior (OR= .99, 97.5% CI = [0.98, 1.02], p=0.688). This result suggests that individual choices were tracked by a Bayesian updating scheme which used their beliefs about the probability as a prior consistent with extensions of the SREU model to reinforcement learning situations.

Table 6. Results of the hierarchical logistic regression for the relationship between individually estimated posteriors and the effect on choice.

	B (SE)	95% CI OR Lower	OR	Upper	p
Intercept	-11.648 (0.906)	<0.001	<0.001	<0.001	<0.001
P(Win)	25.416 (1.758)	3.47×10^9	1.09×10^{11}	3.42×10^{12}	<0.001
Mean (Posterior)	-0.019 (1.184)	0.97	0.98	0.99	<0.001
Std (Posterior)	-0.004 (0.434)	0.98	0.99	1.02	0.688
Mean (Posterior) * Std (Posterior)	0.00 (0.00)	1.00	1.00	1.00	0.573

5.3 AQ is Related to Lower Variance in Beliefs About the Probability but Does Not Predict Choice.

The MMEU model has been used widely to link decisions under ambiguity to various psychiatric disorders and individual differences, including a result showing that the autism quotient (AQ) is positively related to tolerance of ambiguity. However, we hypothesized that these individual differences may be reflective of individual differences in beliefs, for which MMEU is insensitive. To explore this relationship, we first attempted to replicate this relationship by entering AQ into a hierarchical logistic regression along with probability of winning the risky lottery to predict choice for each distribution. We were unable to replicate this effect using the total AQ score (all p>0.05) as well as each of the subscales (all p>0.05). This suggests that means that we were not able to identify if individuals with autism are more or less averse to ambiguity.

Though there was no relationship revealed between individual choices and AQ scores there may still be a relationship between AQ scores and the reported variance in beliefs. To examine this relationship, we used Kendall's tau (Newson, 2002) as our data was non-normally distributed and Kendall's tau provides a statistic with smaller gross error sensitivity and smaller asymptotic variance (Croux & Dehon, 2010) than Spearman's rho which is also commonly used to identify correlations for non-normally distributed data. The total AQ score was negatively correlated with the variance reported for the narrow distribution (τ=-0.127, p=0.002), but positively correlated with variance reported for the wide distribution (τ=0.087, p=0.038) (Figure 9). AQ scores were not related to variance reported for the skewed (τ=-0.033, p=0.436. This result suggests that while autism traits are not necessarily related to choosing ambiguous over risky options, these traits do influence how individuals construct beliefs about the distribution of probabilities. This result may also suggest an interaction between autism traits and their beliefs and preferences to influence more neutral choices.

To ensure we explored the component nature of autism, these correlations were repeated for each subscale of the AQ revealing significant relationship between the standard deviation of the reported variance of the narrow distribution and the Social, Communication, and Attention Switching subscales (reported in table 7).

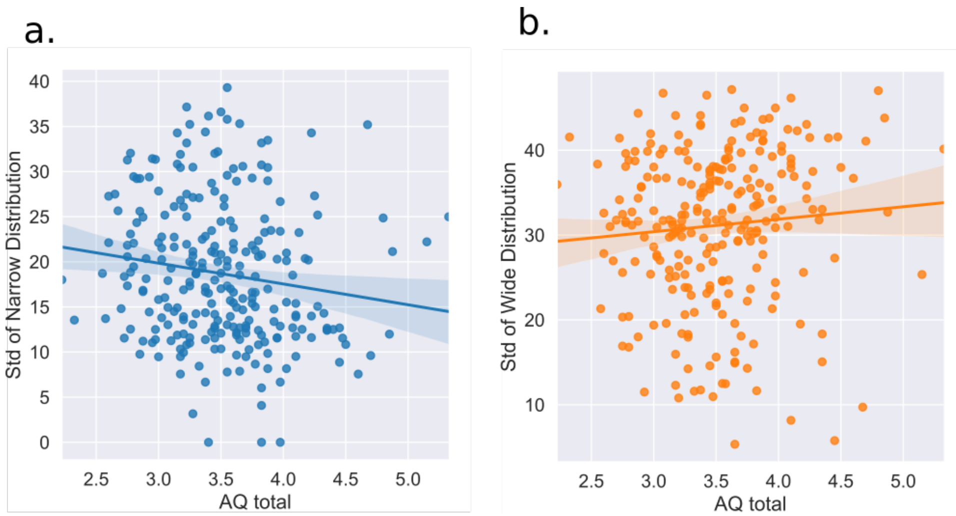

Figure 10. Scatter plots with fitted regression lines and 95% confidence bands describing the relationship between the AQ total score and the standard deviation in reported distributions. Regressions for the narrow (a.) and wide (b.) distributions.

Table 7. The Kendal tau correlation coefficient between the Standard deviation of each of the reported distributions and each scale of the AQ.

Subscale	Std(Narrow)	Std(Wide)	Std(Skewed)
Social	-0.12 **	0.019	-0.026
Communication	-0.13 **	0.077	-0.003
Attn. to Detail	0.014	0.052	-0.087
Attn. Switching	-0.108 *	0.081	-0.040
Imagination	-0.062	0.051	0.056
AQ Total	-0.13 **	0.087*	-0.033

*p<0.05 **p<0.01

Lastly, we ran a mediation analysis to see if any of the variance between AQ and choices between the risky and hidden lotteries could be explained by the relationship between AQ and individual differences in beliefs. The mediation included the total AQ score as the predictor variable, the standard deviation of the reported beliefs as the mediator variable, and the equivalence point as the outcome variable estimated for each participant using the procedure described in 5.2. Mediation models were run separately for the wide and narrow distribution as we found a significant relationship between AQ scores and variance in the reported distributions for both. No indirect relationships were found between AQ scores and the equivalence points for either the wide ($p=0.97$) or narrow ($p=0.83$) distribution. Mediation models were again run for each of the subscales to identify if a particular component of the AQ may be responsible for any relationship between the total AQ and choice however no direct or indirect relationship were found in these analyses (all $p>0.05$).

This project had 3 sets of hypotheses to test whether individuals incorporate beliefs about the distribution of probabilities to make choices under ambiguity. We found evidence that these beliefs influence choice under conditions of full ambiguity and in the early stages of reinforcement learning as ambiguity resolves. While we did not find evidence that individual differences in the believed distribution of probabilities was responsible for the relationship between the autism quotient and choices under ambiguity, we did find evidence that autistic traits were significantly related to how individuals construct beliefs about the distribution of probabilities.

CHAPTER 6:
DISCUSSION

The maxmin expected utility (MMEU) model (Gilboa and Schmeidler, 1989) has been widely applied to psychological research to explain the processing of outcomes with unknown probability (i.e., ambiguity) but does not allow for the incorporation of beliefs which is central to some newer models such as subjective recursive expected utility (SREU) (Klibanoff et al., 2005). We pose four different tests meant to find experimental evidence that ambiguity aversion is driven by the believed variance in the distribution of probabilities, falsifying and demonstrate wider implications by linking beliefs about the distribution of probabilities to another decision context (i.e., reinforcement learning) as well as a clinical variable of interest (i.e., the autism quotient).

Throughout our experiment we found evidence that beliefs about the distribution of probabilities played a significant role in decision-making. Experimental manipulations of the distribution of probabilities were a significant influence on choice and mediated by individual differences in the reported beliefs about the variance of the distribution of probabilities. The mediation of our experimental manipulation is compelling evidence that human decision makers violate basic axioms of MMEU by demonstrating that individuals do incorporate a belief about the probabilities to make decisions under conditions of ambiguity. In response to feedback, we found that a Bayesian updating scheme of those beliefs tracked individual changes in choice in response to feedback. Lastly, while we were unable to reproduce a previously reported relationship between the AQ and choices under ambiguity, we found that the AQ was related to individual differences in the variance of the believed probabilities. Together these results suggest not only a falsification of the MMEU model, but also provide burgeoning evidence for the utility of other models for understanding psychiatric disorders by recovering parameters that can reflect individual beliefs under conditions of ambiguity.

Table 8. A table describing which of the four tests and predictions under MMEU and SREU.

Test	Model predicting results
1. Aversion to Variance in Probability: Direct Experience	**SREU**: A direct association with different distributions of probability had an influence on choice mediated by individual beliefs.
2. Aversion to Variance in Probability: Normalized Experiences	**MMEU**: Order of experience influenced individual reports of the believed distribution of probabilities but did not influence choice.
3. Faster learning under higher variance distributions.	**SREU:** Participants made larger changes in their decisions in response to feedback for stimuli associated with greater variance in probability.
4. Individual Differences: Autism Quotient	**No relationship observed:** No relationship between AQ and choices under ambiguity was observed to determine if this relationship was mediated by beliefs. However, AQ scores were associated with disturbances in the construction of these beliefs.

6.1 Connections and Significance for Judgment and Decision Making

Previous results from psychology and neuroscience studies exploring choices under ambiguity often use a combined approach using hidden lottery stimulus which only manipulates the range of probabilities, (Levy et al., 2012), and the maxmin expected utility model to quantify ambiguity preferences (e.g., Levy et al., 2010; Tanaka, et al., 2015; Raio et al., 2022). Additionally, much of these results relied on the maxmin expected utility model to quantify ambiguity preferences. Using this combined approach participants are often found to treat hidden lotteries with a range of probabilities centered at 50% as though they represent less than a 50% chance of leading to a positive outcome (Chapman et al., 2023, Levy et al., 2010). Even though most individuals tend to be both averse to risk, where the probability of outcomes is known, and ambiguity, the study of these two phenomena have suggested that these preferences are unrelated (Levey et al., 2010; FeldmanHall 2016; Chapman et al., 2023).

Further speaking to the dissociation between risk and ambiguity there have been a wide variety of effects and relationships unique to choices under ambiguity as compared to risk. For example, neuroimaging studies had identified the unique involvement of the lateral prefrontal cortex (Huettel et al., 2006; Levy et al., 2010) and medial temporal lobe (Lopez-Paniagua & Seger, 2013., Brevers et a., 2015) in choices under ambiguity. some studies have suggested that stress uniquely distorts risk and not ambiguity preferences (Buckert et al., 2014) though this has not been consistently replicated (Sambrano et al., 2022). Lastly, numerous individual differences have been related to differential effects of risk and ambiguity aversion including age (Tymula et al., 2012), cumulative lifetime stress exposure (Raio et al., 2022), gambling disorders (Brevers, et al., 2012), and more (Pushkarskaya, et al., 2015; Fujino et al., 2017; Harpaz-Rotem, et al., 2017).

While many of these studies found that individuals were averse to increasing the range of probability, if ambiguous decisions use a mechanism similar to what is described by SREU, the range becomes confounded with the variance in the underlying distribution (Klibanoff et al., 2005). This means that all the effects attributed to ambiguity averse preferences cannot be disentangled from a belief with greater variance in the probabilities. The few studies which had focused on how choice behavior was related to the variance in probability used explicit manipulations describing the distributions and found that ambiguity aversion increased with larger variances in probability (Halevy, 2007, Dean and Ortoleva 2019; Gillen, Chapman et al., 2023). However, these at best suggest a correlation between choices under conditions of ambiguity and known variances in probability.

To combat this problem our study used an implicit manipulation of participants' believed variance in the distribution of probabilities and measured how that belief affected their choices when that information was hidden from them. However, in contrast to both studies manipulating the range of probabilities and the explicit variance in probabilities, we found that our sample was generally ambiguity seeking and displayed greater preference for larger variances in ambiguity. This also deviated from the results we observed in our pilot data where participants were both averse to ambiguity in general and more averse to high variance distributions. One reason for this departure might have been that our sample was matched to a representative sample of the U.S. population on key demographics which may have not been done for previous in person studies. However, results from another recent study using online data collection (Chapman et al., 2023), found that while ambiguity aversion may be less common than what is typically observed from in person experiments, the majority of participants, 71%, were ambiguity averse, with 68% averse to compound risk (a measure related to the explicit variance in probabilities). We do not know whether the difference in ambiguity preferences we observed in our data was due to the structure of the task, the payout mechanisms, or some unidentified difference in our samples (culture etc.). Despite this, our results still show that under conditions of ambiguity people construct a belief about the distribution of probabilities and value ambiguous outcomes based on the variance in that believed distribution. This effect demonstrates that human decision makers do not value ambiguous outcomes with a rule like MMEU.

This work also expanded the role of beliefs about the distribution of probability into the domains of reinforcement learning and individual differences. During reinforcement learning, decision makers have been shown to resolve ambiguity with continued feedback (Hayden et al., 2010, Güney & Newell, 2015) and both MMEU (Gilboa and Schmeidler, 1993) and SREU (Hanay and Klibanoff, 2009) had been extended to suggest how decision makers might resolve this ambiguity. To our knowledge this is the first study which tests whether beliefs about the variance in probability interact with reinforcement feedback in a way that violates extensions of MMEU. We show that beliefs with greater variance are more sensitive to feedback information and that updated choices reflect a Bayesian learner updating their beliefs about the distribution of probabilities. This violates the extensions of MMEU and is consistent with SREU.

As a part of accomplishing the overall aims of our project we attempted to use the reported relationship between autism spectrum traits and ambiguity tolerance, identified using the MMEU model (Fujino et al., 2017) as a vehicle to show the utility of an SREU model by exploring two competing sets of results. While autism spectrum disorder (ASD) is linked to increased tolerance of ambiguity using economic measures, individuals with ASD tend to display more restricted and repetitive behaviors which had also been linked to an increased self-report of intolerance of uncertainty in ASD (Wigham, et al., 2015).

Within our data, we did not find that ASD symptoms are related to decisions under ambiguity. However, we may have identified an important intermediary feature which could help us understand the different relationships between ASD and economic ambiguity and self-reported intolerance to uncertainty. Our results showing that ASD was related to lower variance beliefs would be consistent with more ambiguity neutral choices found in Fujino et al. as well as reports of slower feedback learning (Goris et al., 2021, Sapey-Triomphe, et al., 2022), and still allow for more averse preferences implied by the greater intolerance to uncertainty. Interestingly, this feature was not consigned to just the non-social factors like Attention-Switching but also correlated with the Social and Communication factors. This may imply that how individuals form beliefs is a feature of autism not well captured by the factor model of the AQ or may help to connect both social features and the restrictive and repetitive behaviors which are together have been a hallmark of ASD (Lord et al., 2018).

6.2 Limitations

Our results demonstrate several violations of the MMEU model and suggest that beliefs under ambiguity may be useful indicator or feature of mental health and maladaptive decisions. However, there are weaknesses that we did not foresee. First, though our novel manipulation allows for stronger causal claims about the relationship between beliefs and choices under ambiguity, it makes it difficult to compare our results with those from previous studies. Our study allowed participants to learn the distribution of probabilities in one task and apply that knowledge in another. While we saw that participants treated high and low variance distributions differently, we found that participants preferred high variance distributions which was unexpected. Most studies which observe typically ambiguity averse decisions have no manipulation of these beliefs but simply how much is hidden from participants (Levy et al., 2012). However, previous studies which do describe these probabilities explicitly have seen that individuals tend to be averse to variance in the distribution of probabilities (Halevy, 2007; Chapman et al., 2023). This leaves the possibility that our manipulation significantly changed the nature of the decision in a way we have not accounted for.

Additionally, while our results showed a significant interaction between the learned distribution and a single piece of positive or negative feedback, in typical reinforcement learning paradigms, there may be hundreds of rounds of feedback (Drummond and Niv, 2020). This leaves open the possibility that the role of prior beliefs may decrease with continued feedback. In fact, our hypotheses and results taking a Bayesian approach suggest that after each round of consistent feedback the new prior should have lower and lower variance. This means that in a typical reinforcement learning experiment where feedback is consistent, we would expect that beliefs have smaller roles in future decisions. Lastly, one of the major strengths of MMEU was the simplicity of applying a generative model to a task with the ability to extract reasonable parameters. Finding a combination of task and computational forms that allow for good parameter recovery and fits real world data can be difficult (Wilson and Collins, 2019). Previous results using computational models have been sensitive to small changes in instruction (Feher da Silva & Hare, 2020) and even the addition of a single additional parameter (Palminteri, 2023). In particular, as beliefs and preferences may compete to create similar sets of choices (e.g., ambiguity-neutral decision makers with high variance beliefs vs. Ambiguity-averse decision makers with low variance beliefs), we expect that the task we use will need design changes for similar applications as has been used with MMEU.

6.3 Future Studies

Despite the limitations we discuss, our results present a set of compelling questions for future research. Our results suggest that future studies aiming to separate the role of beliefs and preferences under ambiguity need to include either a similar manipulation of beliefs as we have presented and link it to behavior in more traditional tasks or simply include a measure of beliefs under ambiguity. Both steps would help to disentangle the role of beliefs and preferences in ambiguous decisions. The utility of including this simple measure may be shown by some of our negative results. While we were unable to identify a relationship between AQ and ambiguity preferences using choices under ambiguity, because we included a measure of participants' beliefs about the distribution of probability, we were still able to link AQ to participants' subjective experience during the task. This result suggests that the relationship between ambiguity and other individual differences may be missed without such a measure.

We would also suggest that the link between choices under ambiguity and reinforcement learning be further explored. Despite our suggestion that during reinforcement learning the believed variance the distribution of probability may play a diminishing role with continued and consistent feedback; this belief may be important for other aspects of reinforcement learning. In particular, a belief about the distribution of probability may help us understand how decision makers deal with uncertainty about the decision maker's current state and when a decision maker should switch strategies (Drummond and Niv, 2020). Typically, cases with uncertainty about the decision maker's state become equated to cases with complete knowledge of the state, except that the state is redefined to be a belief with efficiently compounding probability (Dayan and Daw, 2008). Our results suggest that we can no longer assume efficiently compounding probability following the redefinition of state uncertainty and differential probabilities under those uncertain states may lead to novel behavior. Our results also have implications for how individuals switch strategies in cases of reinforcement learning. These implications could be easily explored using a reversal learning paradigm (Izquierdo, et al., 2017). In a reversal learning task, a consistently reinforced stimuli suddenly stops being reinforced to see how long it takes for participants to change their behavior (Izquierdo, et al., 2017). If this stimulus is also paired to a high variance distribution in probability, our results suggest that participants should more quickly adapt to these changes. This would suggest that there is a dynamic interplay of beliefs and that includes multiple priors to determine learning behavior.

Lastly, our results highlight a need for the simulation and design work would allow for more accurate analysis of individual parameters, the incorporation of additional variables (e.g., reaction times, eye movements and neural data) and allow for more widespread adoption of the model in analyses and existing statistical packages (Haines et al., 2023; Wilson and Collins, 2019). While we cannot say for certain what factors will allow computational modelling of an SREU class of models, there are two changes to the typical hidden lottery task that may help. First, while the typical hidden lottery task hides some portion of the lottery in a way that is symmetrical around 50%, by moving this range up or down (e.g., 0%-50%, 50%-100%) we may be able to capture sensitivity to the mean of our beliefs. For example, a decision maker who has low variance beliefs that chance of winning is around 40% may not make different choices for a range that covers 0%-50% or 25%-75% but will for a range that covers 50%-100%.

Lastly, as we saw, a single piece of reinforcement feedback has a larger effect on high variance beliefs and should influence individuals similarly despite different ambiguity preferences. Finding a task that allows for good model fitting and parameter recovery would help for wider spread exploration of these constructs.

6.3 Conclusions

In contrast to the axioms of maxmin expected utility, our results clearly show that individuals do construct and incorporate a belief about the distribution of probabilities when making decisions under ambiguity. The combination of experimental manipulation and mediation analysis demonstrates a likely causal relationship between the variance in beliefs about the probability and choices under conditions of ambiguity. While our sample was unique in displaying significant preferences rather than aversion to the wider variance distribution, this behavior is still consistent with the kinds of mechanisms described by SREU and is inconsistent with those of maxmin expected utility. We hope that future work can better explore how to directly model this behavior, incorporate physiological variables, and link ambiguity to other domains of decisions.

Additionally, we show that these beliefs are related to clinical variables of interest but may have gone undetected using the traditional ambiguous decision tasks in combination with the MMEU model. This also leaves significant work in exploring whether previously observed differences in choices under ambiguity using MMEU should be attributed to preference or beliefs. Lastly, these open exciting opportunities for understanding what traits of psychiatric illness may play a role in maladaptive decisions.

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APPENDIX A
PILOT STUDY

In Chapter 2 and 3 of this manuscript, we reference a pilot study conducted as part of a larger neuroimaging study already being performed. Below we briefly describe the methods and results of this pilot study, highlighting where there are differences and departures from the online study described in the body of the manuscript.

A.1 Methods

A.1.1 Participants

A total of 53 participants [12 females; age: mean (M) = 20.9years, (SD) = 1.8 years] completed the experiment. Participants gave written informed consent as part of a protocol approved by the Institutional Review Board of Temple University. The same exclusion criteria were applied as described in the analysis plan of the main text (section 4.1). For a more detailed breakdown of race and sex see Table below.

Table A1. Demographic information about the sample. The number of individuals in the sample and percent of the (to the nearest whole percent) is listed for each uniquely indicated sex, race, and level of education.

	Sex		
Race	Male	Female	Total
White or Caucasian	22	5	27

Table A1 continued

Black or African American	2	0	2
Asian or Pacific Islander	13	5	18
Multiple or Other	4	2	6
Total	41	12	53

A.1.2 Procedures

Data collected as part of the pilot study was collected from a convenience sample of individuals performing a “mock scan” as part of a larger neuroimaging experiment. All data presented here was collected between one and two weeks prior to participants' real scan date and outside of the scanner. Participants were informed that on the date of their scan they would be paid $25 and hour for their time inside the scanner and $15 an hour for their time outside of the scanner as well as a bonus between $0-$150 based on their performance across several tasks including their decisions from the linked colored lottery task described below.

A.1.2.1 Linked Colored Lottery tasks

After their mock scan procedure was completed, participants performed a version of the linked colored lottery task as described in the body of the manuscript with four major departures. First, during the risky colored lottery task the order of distribution was completely randomized where during the online study there was a set of four random orders. Second, during the hidden colored lottery task, participants made decisions about an additional colored lottery which was not introduced in the risky colored lottery task. This means that for the last hidden lottery color the underlying probability was unknown to the participants. Third, during the hidden colored lottery task, the probability of the risky lottery was not “staircased” as it was in the online sample. Instead, participants made decisions between the hidden lottery and a set of eight risky lotteries with the probabilities ranging from 20% - 90% in steps of 10%. This means that all participants were presented with the exact same decisions. However, the resolution for which participants traded off the known risks and hidden lotteries is reduced compared to the online sample. Lastly, a feedback version of the task was not introduced in the pilot study.

A.1.2.1 Questionnaires: Autism Spectrum Quotient

As described in the main text, participants answered the Autism Spectrum Quotient Questionnaire (AQ). However, there are two major departures from how this was conducted in the online experiment. First, during the online experiment the AQ was completed right away within a few minutes of the tasks described. In the pilot study participants completed the AQ as a part of a battery of questionnaires to be completed between the mock scan and MRI scan date one to two weeks apart. In addition to the AQ this battery included the Adolescent Alcohol and Drug Involvement Scale (Moberg, 2003), Seven up Seven Down Inventory (Youngstrom et al., 2013), Trait Emotional Intelligence Questionnaire (Petrides, 2009), Interpersonal Reactivity Index (Davis, 1980), Temporal

Experience of Pleasure Scale (Gard et al., 2006), Altman Self-Rating Mania Scale (Altman et al., 1997), Positive Valence System Scale (Khazanov et al., 2019), and Personal Norm of Reciprocity questionnaire (Perugini et al., 2003). Data from these additional questionnaires was not analyzed in relationship to behavior during the linked colored lottery task but may have provided a different context in which the AQ was answered in the online study.

A.2 Results

A.2.1 Perceived Variance in Probabilities Decreased Preference for Ambiguity

Similar to the online study, we first conducted a manipulation check to ensure that experienced and order of distribution affected reported beliefs about the distribution. As expected, participants reported distributions had greater standard deviation in the wide as compared to narrow distributions ($t(42) = 4.54$, $p<0.001$). As with the online experiment, we tested if participants who made decisions about the narrow distribution before the wide distribution would report greater variance in the wide distribution and found they did ($t(42) = -2.74$, $p=0.009$).

As an added check on the accuracy of these ratings we conducted two correlations, finding a significant relationship between the means that individuals reported for each distribution and the true mean ($r=0.68$, $p<0.001$) as well as the standard deviation that individuals reported for each distribution and the true standard deviation of those distributions ($r=.64$, $p<0.001$). However, we also found that individuals significantly overestimated the mean of the wide distribution (t=2.07, p=0.034) and underestimated the means of the narrow (t=-2.19, p=0.033) and skewed distribution (t=-5.08, p<0.001). Additionally, participants tended to overestimate the standard deviation of the narrow (t= 6.53, p<0.001) and skew (t= 5.23, p<0.001) and underestimated the variance of the wide distribution (t=-5.51, p<0.001)

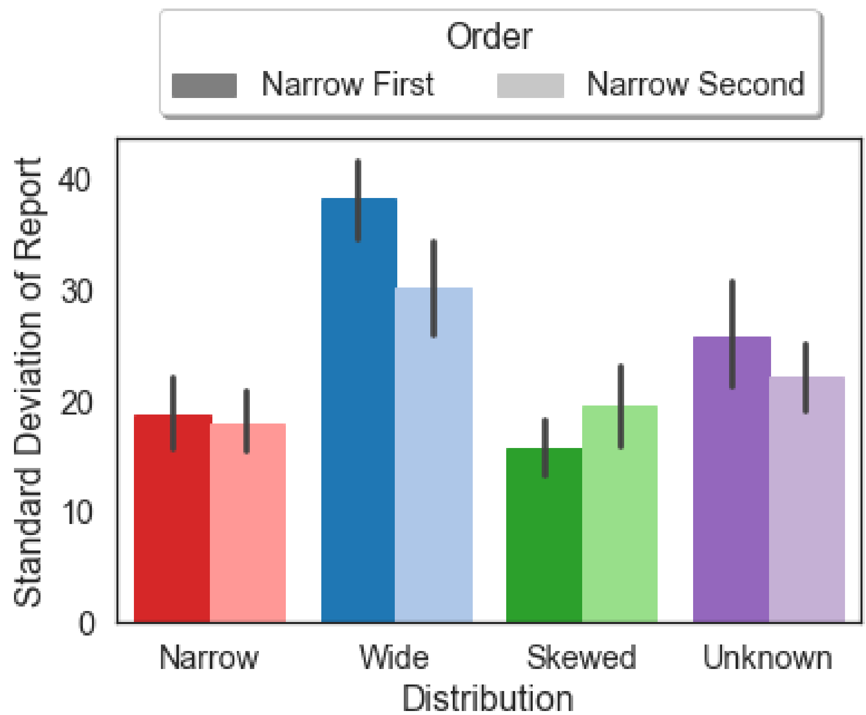

Figure A1. Participants reports showed that they remembered seeing greater variability in the chance of winning for the color lottery associated with the wide condition as compared to the Narrow and Skewed conditions. Participants who experienced the narrow condition before the wide condition reported greater variability in the chance of winning for the color lottery associated with the wide distribution.

As in the online study we evaluated if participants were more averse to ambiguous lotteries associated with wide (high variance) as compared to narrow (low variance) distributions using a hierarchical logistic regression (see table A2).

We found that making choices about the wide distribution significantly decreased the chance of choosing the risky lottery over the hidden lottery (OR= 1.11, 95%CI= [0.788 ,1.5]) (Figure 7). These results are consistent with previous literature showing that individuals are averse to both ambiguous outcomes and variance in the believed probabilities.

Figure A2. Logistic regression for the effect of the probability on winning the risky lottery on choosing the risky over the hidden lottery drawn separate for each distribution. The grey lines represent the optimal switching point for an ambiguity neutral decision maker. Regression lines which cross the horizontal line to the left of the vertical are ambiguity averse while those crossing to the right are ambiguity seeking.

Table A2. Results of the hierarchical logistic regression for the effect of distribution on choice.

		95% CI OR			
	B (SE)	Lower	OR	Upper	p
Intercept	-3.467 (0.420)	0.014	0.031	0.071	<0.001

Table A2 continued

P(Win)	8.732 (0.362)	1.072	1.090	1.109	<0.001
Distribution	-0.276 (0.050)	1.416	4.070	11.699	0.009

We also used a logistic regression to test the effects of order on choice, the results of which are reported in table A3. Here, we also found that those who had seen the narrow lottery first (associated with greater variance) were more averse to the wide distribution than those who had experienced the narrow distribution second. This suggests the effect of order presentation in the risky decision phase on variance in probability did not translate to an observable effect on choice behavior.

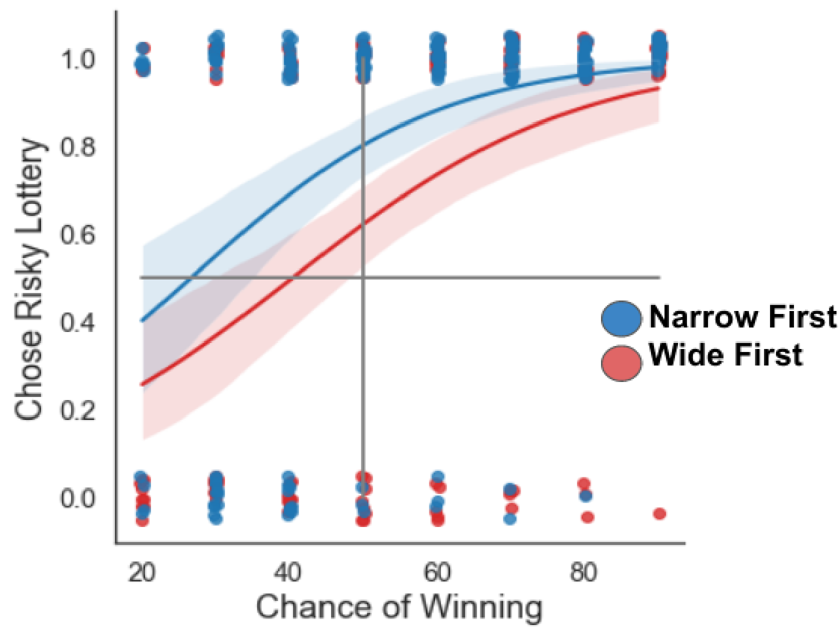

Figure A3. Logistic regression for the effect of the probability on winning the risky lottery on choosing the risky over the 'wide' hidden lottery drawn separate for each order group.

Table A3. Results of the hierarchical logistic regression for the effect of order on choice.

	B (SE)	95% CI OR Lower	OR	95% CI OR Upper	p
Intercept	-2.53 (0.515)	0.029	0.080	0.219	<0.001
P(Win)	0.061 (0. 009)	1.045	1.063	1.082	<0.001
Order	1.005 (0.407)	1.231	2.731	6.063	0.014

Though we already showed that our manipulations of distribution and order affected both individual reports of the variance and choices in the predicted directions, we followed these results with two mediation analyses. In the first mediation model, we entered the distribution (wide or narrow) as the predictor variable, the variance of an individual's reported distribution for the distribution as the mediator, and their equivalence point as the outcome variable. The equivalence point represents the theoretical probability of winning a risky lottery for which a participant is equally likely to choose the hidden and risky lottery (see section 4.2.1 for details on how this was obtained). Using mediation, we found a significant indirect effect of distribution on choice through variance in beliefs (B (SE) = 0.018 (0.009), 95% C.I. [9×10^{-4}, 3.4×10^{-2}], p=0.036). Our second model again used the variance of an individual's reported distribution for the distribution as the mediator, and their equivalence point as the outcome variable, but instead used the order manipulation (Before or After) as the predictor variable. This time we did not find a significant indirect effect of order on choice through the believed variance of the distribution as the mediator (B (SE) = 0.023 (0.109), 95% C.I. [-0.15, 0.323], p=0.84).

A.2.2 AQ is Related to Lower Variance in Beliefs about the Probability but Does Not Predict Choice

Like the online study, we hypothesized that individual differences in choice previously related to the Autism Quotient (Fujino et al., 2017) may be due to a relationship between AQW and individual differences in the believed variance about the underlying probabilities. To explore this relationship, we first tried to replicate the effect reported by Fujino et al. By entering AQ scores into a hierarchical logistic regression along with probability of winning the risky lottery to predict choice for each distribution. Though we found a significant effect of AQ on choice for the skewed distribution, our results suggested that AQ scores were associated with more ambiguity aversion. Exploring the effects of AQ on choice for the narrow, wide, or additional unknown distribution we saw no significant effects (see table A 4). Together these results suggest that we were not able to replicate the results from Fujino et al., 2017.

Though there was no relationship revealed between individual choices and AQ scores there may still be a relationship between AQ scores and the reported variance in beliefs. To examine this relationship, we used Kendall's tau (Newson, 2002) as our data was non-normally distributed and Kendall's tau provides a statistic with smaller gross error sensitivity and smaller asymptotic variance (Croux & Dehon, 2010) than Spearman's rho which is also commonly used to identify correlations for non-normally distributed data. The total AQ score was negatively correlated with the variance reported for the narrow distribution (τ=-0.127, p=0.002), but positively correlated with variance reported for the wide distribution (τ=0.087, p=0.038) (Figure 9). AQ scores were not related to variance reported for the skewed (τ=-0.033, p=0.436. This result suggests that while autism traits are not necessarily related to choosing ambiguous over risky options, these traits do influence how individuals construct beliefs about the distribution of probabilities. This result may also suggest an interaction between autism traits and their beliefs and preferences to influence more neutral choices.

Table A4. Results of the hierarchical logistic regression for the effect of AQ on choice.

	B (SE)	95% CI OR Lower	OR	Upper	p
Choices for Narrow					
Intercept	-4.546 (1.079)	0. 001	0. 011	0. 088	<0.001
P(Win)	0.125 (0. 020)	1.090	1.133	1.178	<0.001
A.Q.	-0.028 (0. 035)	0.907	0.972	1.042	0.428
Choices for Wide					
Intercept	-5.001 (1.268)	0.001	0. 007	0. 081	<0.001
P(Win)	0.102 (0.020)	1.064	1.107	1.152	<0.001
A.Q.	0.065 (0.037)	0.992	1.067	1.148	0.082
Choices for Skew					
Intercept	-11.410 (0. 001)	0.029	0.080	0.219	<0.001
P(Win)	0.16 (0. 001)	1.013	1.010	1.015	<0.001
A.Q.	0.013 (0. 001)	1.171	1.173	1.176	<0.001
Choices for Unknown					
Intercept	-6.045 (1.225)	0.000	0.002	0.026	<0.001
P(Win)	0.129 (0.019)	1.096	1.138	1.183	<0.001
A.Q.	-0.006 (0. 040)	0.919	0.994	1.075	0.879

To ensure we explored the component nature of autism, these correlations were repeated for each subscale of the AQ revealing significant relationship between the standard deviation of the reported variance of the narrow distribution and the Social, Communication, and Attention Switching subscales (reported in table 7).

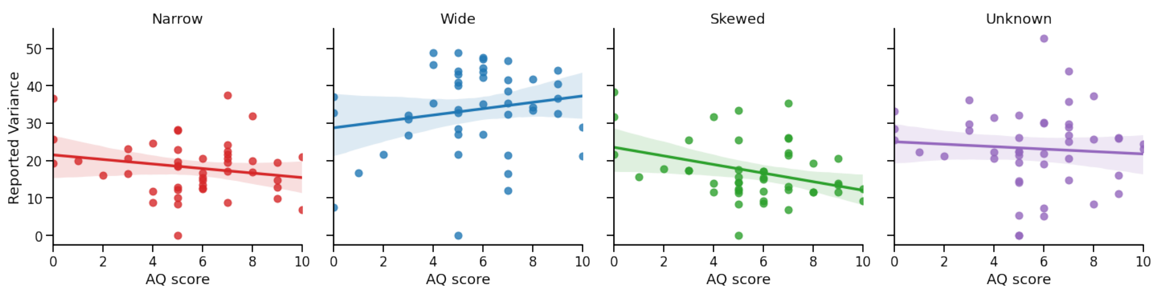

Figure A4. Scatter plots with fitted regression lines and 95% confidence bands describing the relationship between the AQ total score and the standard deviation in reported distributions of the narrow, wide, skewed, and unknown distributions.

Table A5. The Kendal tau correlation coefficient between the Standard deviation of each of the reported distributions and each scale of the AQ.

Subscale	**Narrow (Std)**	**Wide (Std)**	**Skew (Std)**	**Unknown (Std)**
Social	-0.004	0.079	-0.17	-0.09
Communication	-0.085	0.106	-0.144	0.0
Attn. to Detail	0.072	-0.109	-0.14	-0.09
Attn. Switching	-0.076	0.063	**-0.21***	-0.043
Imagination	-0.039	-0.031	-0.12	-0.026
AQ Total	-0.082	0.026	**-0.249***	-0.059

*p<0.05 uncorrected

Lastly, we ran a mediation analysis to see if any of the variance between AQ and choices between the risky and hidden lotteries could be explained by the relationship between AQ and individual differences in beliefs. The mediation included the total AQ score as the predictor variable, the standard deviation of the reported beliefs as the mediator variable, and the equivalence point as the outcome variable estimated for each participant using the procedure described in 5.2. Mediation models were run separately for each distribution as well as the total AQ and for each of the subscales of the AQ however no direct or indirect relationship were found in these analyses (all $p>0.05$).