# Time Pressure as an Amplifier of Information Preferences in Risky Decision Making

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## Abstract

The aim of the current thesis was to investigate the effect of time pressure on information utilization in risky decisions. Multiple trials of a risky choice task, where four information-cues indicated whether a gamble should be accepted or rejected, were performed while time pressure was manipulated within subjects. Information preferences were measured separately for each subject, using mixed effects regression analyses on both eye tracking- and behavioral data. Two competing hypotheses were proposed for how time pressure would influence information use. The loss-hypothesis, based on conclusions drawn in prior studies, predicted that time pressure would increase risk aversion, and lead to increased reliance on information about negative outcomes. The focus narrowing-hypothesis, novel to this study, predicted that time pressure would increase reliance on the information considered the most central to performing the task, and decrease reliance on the information deemed least central. The effect of time pressure would then depend on how the decision maker evaluated the relative importance of the four pieces of information in the task. The results were inconsistent with the loss-hypothesis. The increased overall tendency to prioritize information about the probability of positive outcomes under time pressure suggested that the willingness to take risks went up rather than down. In contrast, the results were consistent with a focus narrowing effect of time pressure in risky decisions. The effect of time pressure is thus suggested to interact with the characteristics of the decision maker, by amplifying pre-existing information preferences.

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# Introduction

Many decisions we make, whether big or small, involve an element of risk. Deciding to tell a joke involves the risk that your audience finds it unfunny. Deciding to undergo surgery to treat epilepsy entails risks of reduced cognitive- and motoric functioning. Risky decision making is the process of weighting risks against rewards when choosing between alternatives with uncertain outcomes.

In the terminology of risky decision research, desirable outcomes of a risky choice are called “gains” and the unwanted outcomes are called “losses”. All gains and losses can be evaluated along two separate dimensions: the magnitude dimension and the probability dimension. Magnitude refers to how positively/negatively a gain/loss would be experienced if it was to occur. Winning the grand prize in the lottery is a gain with a larger magnitude than the other prizes. Losing your little toe in an accident is a loss of smaller magnitude than losing your entire foot. The second of the dimensions, probability, simply refers to how likely a particular outcome is to occur. The grand prize typically scores lower than the other lottery-prizes on the probability dimension.

All four information-dimensions in risky choices, magnitudes and probabilities of both gains and losses, are important for making good decisions. What dimensions most strongly influence decisions can vary depending on characteristics of both the decision maker and the situation. Some people tend to focus on maximizing the potential gains of their choices, paying less attention to the risks (Lauriola & Levin, 2001). However, evidence suggests that the majority of people are loss averse across most situations: They are more concerned with avoiding losses than with obtaining gains of equivalent magnitudes, meaning that information about losses tends to carry more weight in their decisions (Kahneman & Tversky, 1992).

How we actually make risky decisions – how we assess and compare gains and losses, and how we arrive at a choice – has been extensively studied. Several theoretical models have been developed, and studies are continuously being carried out where models are compared on how well they are able to predict the choices people make on risky decision-tasks (see e.g., Birnbaum, 2011).

One feature that is common to most examinations of decision making under risk, is that decision makers can take as much time as they like in making their choices. However, in the real world, the window of time for making a risky decision can often be quite short. Such as when a surgeon has to react to a sudden dangerous problem, or when a trader in a financial market needs to make orders within seconds after new information becomes available (Busse & Green, 2002).

The lack of research and theory on the influence of time pressure on risky decision making is not due to a lack of acknowledgment that contextual factors like time pressure could have a real impact on the decision process. It is with reference to such factors that theorists typically justify the great amounts of flexibility they incorporate into most models, in the form of parameters that are free to vary (Birnbaum, 2008). Additionally, knowledge of the influence of time pressure on risky decisions is of value to the emerging field of neuroeconomics, which uses neuroimaging to study the neural correlates of value-based decisions including decisions under risk. Neuroimaging experiments typically require quite restricted time-limits for each trial, meaning that the generalizability of neuroeconomic findings on risky decision making depends on the extent to which time pressure has an influence on the process.

The few existing studies on the effect of time pressure on risky decision making mostly conclude that time pressure seems to have a general effect of reducing decision makers' willingness to take risks. People are suggested to become even more concerned with keeping the magnitudes and probabilities of losses as small as possible, either because time pressure causes the negative impact of losses to be felt more strongly (Bollard, 2007), or because they get an increased desire to keep the outcome of their choices predictable (Ben Zur & Breznitz, 1981). This idea that time pressure causes increased reliance on information about losses in risky decisions will be referred to as the "loss-hypothesis".

The aim of the current thesis is to test novel predictions from an alternative interpretation of the prior studies. This alternative interpretation, which will be referred to as the "focus narrowing-hypothesis", is based on findings from research on riskless multi-attribute choices (e.g., Maule & Edland, 1997) as well as research on the effects of stressors such as time pressure on attentional selectivity (e.g, Chajut & Algom, 2003; Mather & Sutherland, 2011). Rather than time pressure causing a general effect of increased reliance on the loss dimensions, as described by the loss-hypothesis, it is predicted that time pressure has the effect of narrowing the decision maker's focus on whatever dimensions are considered the most central to the task. The effect of time pressure is thus hypothesized to interact with the preferences of the decision maker. Time pressure increases reliance on what is already relied on the most, and decreases reliance on the information relied on least.

As the majority of decision makers presumably are most concerned with avoiding losses (Tversky & Kahneman, 1992), the two competing hypotheses make similar (though not identical) predictions for the effect of time pressure in most cases. But for decision makers who rather prioritize maximizing the magnitudes and/or probabilities of potential gains, the predictions from the two hypotheses clearly differ.

Prior studies have not investigated the possibility of this kind of interaction between time pressure and individual preferences in risky choices. Most prior studies have used between subject designs, making the necessary analyses impossible. When group-averages are compared, the tendency for participants to be loss averse would mask any effects of time pressure in the opposite direction on those who are not loss averse.

The present study uses a within subject design, where each participant performs a risky choice task under both low- and high time pressure. How much participants rely on the different pieces of information in the task is measured using eye tracking in conjunction with analyses of the choices made. Separate estimates of information preferences are made for each participant through the use of mixed effects regression analyses (Hox, 2002). The within subjects manipulation of time pressure allows investigating whether the preferences shown under low time pressure indeed predict how information reliance changes when time pressure is increased.

In the remainder of the introductory section of this thesis, I will first explain some key terms. I then review prior studies on the effects of time pressure on risky decision making, and explain the authors' rationales behind interpreting the results in line with the loss hypothesis. I will then discuss the focus narrowing-hypothesis. I explain how the results from prior studies are consistent with focus narrowing, and I will go through the research on which the hypothesis is based. This includes research on riskless multi-attribute choices, research on the effects of stress on attention, and research on how attention both influences and is influenced by decision making processes.

## Key terms

**Time pressure.** In this thesis, the term "time pressure" will be used as it is defined by Maule and Hockey (1993). Accordingly, time pressure doesn't necessarily exist whenever there is a deadline or some other incentive to complete a task quickly. Time pressure can be said to be present only when (1) the person performing a task is motivated to perform at a given level, and (2) is prevented from reaching this level of performance due to a competing need to perform the task quickly. In sum, there needs to be a feeling of pressure for there to be time pressure. If you can comfortably complete the task at a high level within the deadline, or if you are unconcerned that task performance drops due to the deadline, no pressure is felt, and so no time pressure is present.

**Risk preferences.** Risk preferences describe a person's tendency to seek or avoid risks. Given the choice between gambles that have the same average pay-out in the long run ("expected value"), someone who is risk seeking would go for a high risk-high reward type of gamble. The higher the variability in the possible outcomes of a gamble, the more it is preferred. For example, a risk seeking decision maker would prefer a fifty-fifty gamble where you either win or lose 100$ over a gamble were the amount won or lost is instead 10$, even though the expected value is zero in both cases. Risk aversion, on the other hand, implies that you prefer safer low-risk gambles. The gamble with the 10$-pay outs would then be preferred. If you are risk neutral, then you only care about the expected value. You would then be indifferent between the gambles, since their expected values are the same.

For a risk-averse person to choose a high risk gamble over a low risk gamble, the expected value would have to be adjusted up. The more risk averse you are, the higher the expected value would have to be for you to be willing to accept increased levels of risk. And vice versa for risk seeking; the more risk seeking you are, the more profitable the safe gamble would have to be compared to the risky gamble for you to choose it. People typically tend to be risk averse (Holt & Laury, 2002), but there is considerable variation depending on both personality traits (Lauriola & Levin, 2001) and situational factors (Hausch, Ziemba & Rubenstein, 1981).

Loss aversion differs from risk aversion. While risk preferences describe your attitude towards a prospect's variability in its outcomes, loss aversion refers to your attitude towards losses. For someone who is loss averse, a loss of a given magnitude is felt more strongly than an equally sized gain. This means that losses will influence choices more than gains. The opposite of being loss averse is to be gain seeking; you experience gains more powerfully than losses. When choosing between alternatives that involve both gains and losses, high risk choices tend to have larger potential losses than low risk choices. This means that loss aversion and risk aversion often (but not always) imply the same choice in decisions involving mixed-outcome gambles (gambles that can result in both losses and gains).

The literature suggests that it is more common to be loss averse than to be gain seeking (Tversky & Kahneman, 1992). This is evidenced, for instance, by how stock traders tend to sell winning stocks too early (for fear that they might drop) and hold on to losing stocks for too long (hoping that they might rise) (Shefrin & Statman, 1985).

As time pressure has been shown to reliably induce stress (Maule & Hockey, 1993), effects of stress on risk taking are of relevance to the topic of this thesis. However, the existing literature on effects of stress on risk preferences is inconsistent. There are a number of studies indicating that stress and anxiety lead to decreased risk taking (e.g., Raghunathan & Pham, 1999; Lerner & Keltner, 2000), but others report the opposite effect (e.g., Starcke, Wolf, Markowitsch & Brand, 2008).

**Prior studies on the effects of time pressure on risky decisions**

Ben Zur and Breznitz (1981) used a task of choosing between pairs of two-outcome mixed gambles. The magnitudes and probabilities of the gains and losses were varied between trials in such a way that the expected values of the two gambles were always equal, but one gamble was always more risky than the other. The information about the gambles was displayed on a board which only allowed one piece of information to be inspected at a time, and information utilization was recorded. There were three time pressure conditions; low (32 sec), medium (16 sec) and high (8 sec).

The main findings were that the tendency to choose the safer gamble increased with intensifying time pressure, and so too did the proportion of the decision time that was spent looking at information about losses. The authors suggested that participants became more risk averse under time pressure, and that choosing the safer gamble represented a way to reduce the stress of time pressure

Busemeyer (1985), however, suggested that the effect of time pressure could better be described as increased loss aversion, rather than risk aversion. Loss aversion translates to risk aversion in choice between gambles with mixed outcomes, like those used by Ben Zur and Breznitz. But there are situations where loss aversion can lead to risk seeking behavior. Such as when choosing between a sure loss and a gamble which could yield a larger loss but which could also lead to a gain. Loss averse people are more inclined to make the risk seeking choice of picking the gamble in this case, because the sure loss is so aversive to them.

The task in Busemeyer's experiment involved choosing between a sure amount and an amount drawn randomly from a distribution. The sure amounts were either -3, 0 or 3. The distribution to be drawn from always had a mean of zero (so the expected value of drawing from it was always zero), but its standard deviation could be either high (50) or low (5). Time pressure was found to increase participants' tendency to choose 3 over the high variance distribution (indicating risk aversion), and simultaneously decreased their tendency to choose -3 over the distribution (which implies risk seeking). Both of these results are compatible with increased loss aversion under time pressure: more often choosing a sure positive amount over a draw from a distribution which could potentially yield a loss indicates an increased aversion for these losses. And more often choosing to draw from a distribution which could yield a positive amount rather than accepting a sure loss indicates an increased willingness to take risks to potentially avoid a loss.

The few studies done since Busemeyer's study give partial support to the proposal that time pressure leads to loss aversion. Bollard et al. (2007) found increased risk aversion in a task of choosing whether to buy participation in gambles that had a varying probability of yielding a gain of 1$, otherwise yielding zero. But the effect has since been suggested to possibly having been driven by an increased utilization of the posted buy-in price as a cue to gamble-attractiveness under time pressure, rather than loss aversion (Nursimulu & Bossaerts, 2014). Expensive gambles, which were bought significantly more often under time pressure, tended to have a larger probability of winning, meaning that the variability in their possible outcomes (and thus their level of risk) was lower. But the loss incurred if the gamble didn't pay (i.e. the buy-in price) was larger in these instances.

Kocher, Pahlke and Trautmann (2013), investigated the effects of time pressure on a large range of different kinds of gamble choices. A subset of the choices were between a pure gain gamble (only gain-outcomes are possible) and a mixed gamble with a higher expected value than the gain gamble. Consistent with increased loss aversion, participants were substantially more likely to choose the loss-free gain prospects under time pressure.

On another subset of the gamble-choices, however, participants displayed gain seeking, the opposite of loss aversion. These were choices between pure loss gambles and mixed gambles of lower expected values. The possible loss in the mixed gamble was always larger and/or more probable than the largest loss in the loss gamble. While participants were mostly loss averse in the low time pressure condition, over half of the choices were in favor of the mixed gamble under time pressure. Choosing the mixed gamble despite its expected value being lower implies that the gains weighted more heavily in the decision than the losses, which is contrary to loss aversion.

**The possibility of a focusing narrowing effect**

As stated in the introduction, I propose that the results of prior studies can be equally well accounted for by a focusing narrowing effect, which involves increased reliance on the information considered most central to performing the task. Rather than time pressure causing a general increase in loss aversion, it leads to increased loss aversion only in those who would base decisions mostly on losses if there was no time pressure. As most people are loss averse, group-level analysis are unable to distinguish between these effects.

The focus narrowing effect can also be argued to be able to account for some of the findings that are inconsistent with increased loss aversion. In the case of Bollard et al. (2007), the buy-in price, which was relied on more under time pressure, was the only information that was stated on the screen. The task involved betting on whether the next card drawn from a deck of cards would be higher or lower than the previous card drawn. The prize for winning the bet was always 1$, but the probability of winning depended on what the previous card drawn was. If the previous card was high, the probability of winning would be low. The buy-in price tended to reflect the value of the gamble, though it did vary even for gambles of equal expected value. The only information on screen was the previous card drawn and the buy-in price. The probabilities of winning and losing had to be inferred from the card on screen. As the buy-in price featured so prominently on the screen, it is natural to assume that it featured prominently in peoples decisions as well. The focus narrowing effect would then predict that it would be utilized even more under time pressure, and this is also what the results showed.

Kocher et al. produced increased gain seeking rather than loss aversion under time pressure in a gamble-choice between a pure loss gamble and a mixed gamble of worse expected value. Choosing the mixed gamble was the gain seeking choice. One could here speculate that the gain, being the only gain among three losses, had an advantage in receiving the decision maker’s attention. According to the focus narrowing effect, such a bias would be amplified under time pressure, leading to increased reliance on this gain cue, and thus gain seeking.

**Focus narrowing in multi-attribute decisions.** The proposal of a focusing narrowing effect is inspired by results from studies on multi-attribute decisions under time pressure. A multi-attribute decision involves choosing between or evaluating alternatives on the basis of information about their scores on specific attributes. An example is the process of deciding on what laptop to buy; the different models are compared on battery life, price, screen resolution and so on. Risky decision making can be considered a sub-category of multi-attribute decisions; the risky choice alternatives you are making decisions about have attributes in the form of the magnitudes and probabilities of their gains and losses.

Studies of the effects of time pressure on information usage in multi-attribute choices are more numerous than those investigating the effects on risk preferences. And a result that seems to replicate in most of the studies, across most domains of choice, is that the information that most strongly influences responses in the absence of time pressure has an even bigger impact when time pressure is introduced. Svenson and Edland (1987) looked at how participants rated the attractiveness of apartments on the basis of travel distance to work, standard of build, and size. Travel distance was found to correlate the most strongly with the overall rating given by participants, and this correlation was even stronger under time pressure. Wright (1974) found similar results in a task of choosing between cars that differed in selling price, handling, maintenance cost, styling and comfort. Other tasks used, all producing an effect of increased reliance on the most important attribute under time pressure, include a choice between students for enrollment at a university program on the basis of high school grades (Edland, 1994), a choice between different birth control devices based on attributes such as success rate and price (Wright & Weitz, 1977) and a judgment of category membership on the basis of cues of varying diagnostic value (Wallsten & Barton, 1982).

**Focus narrowing as an effect of stressors on attentional selectivity.** In 1959, Easterbrook published a review of an already substantial amount of studies suggesting that stress, in most of its forms, has the effect of causing attention to become more selective. When stressed, we attend more intently to the information that is currently the most relevant to our goals, and we are less easily sidetracked by irrelevant distractors.

More recent reviews (e.g., Wells & Matthews, 1994; Mather & Sutherland, 2011) have even larger collections of results to base conclusions on. Wells and Matthews stated that “one of the few consistent effects of arousing stressors, which generalizes across different sources of stress is narrowing of attention” (p.187). Importantly, the list of stressors that have been found to increase attentional selectivity includes time pressure (e.g., Bargh & Thein, 1985; Chajut & Algom, 2003; Pratto & Oliver, 1991). Other stress-inducers that have been found to elicit increased selectivity include: loud noise (Hockey, 1970); the presence of observers (Baron, 1986); electric shock (Cornsweet, 1969); and heat (Bursill, 1958). The task set-up typically involves responding to peripheral distractor stimuli while engaged in a main task requiring continuous attention, in which main task performance improves and secondary task performance deteriorates under stress (e.g., Hockey; Bursill). But multiple other paradigms have been used as well.

Among the studies looking specifically at the influence of time pressure on attentional selectivity, it was found that: performance improves on the Garner-task, which measures the ability to ignore irrelevant stimuli (Chajut & Algom, 2003); that impression formation became more strongly based on the most salient information (Bargh & Thein, 1985); and that visual attention focused more on product characteristics and less on pictures and logos in a task of choosing between consumer products (Pieters & Warlop, 1998).

Importantly, the effect of stress on attention is not restricted to visual and auditory attention. As indicated by the results from Hockey and Hamilton, as well as others (e.g., Beilock & DeCaro, 2007; Sutherland & Mather, 2012), stress is likely to also cause increased attentional selectivity among representations in working memory. Stress might then also cause increased focus on what is considered the most relevant among the representations of gains, losses and probabilities that exist in working memory during risky decisions.

## Causal relationships between attention and decision making

Arrows of causal influence seem to go in both directions between attention and decision making. There is good empirical basis for the claim that stimuli that carry more weight in our decision making processes typically will receive more of our visual attention (e.g., Payne, Bettman & Johnson, 1988). And there is also research to suggest that increasing the share of attention a stimulus receives can amplify its decision weight (e.g., Armel, Beaumel & Rangel, 2008). Additionally, it is trivially true that when we completely divert attention from parts of the information when using heuristics, the decision weight on ignored information drops to zero.

Examinations of both directions of causality between attention and decision weight are of relevance to this thesis. Eye tracking is used to measure the importance of information in the decision making process, based on the assumption that important information gets more of our visual attention. And the focus narrowing hypothesis assumes that when stress causes us to increase our focus on some information, this information then influences our choices more strongly. These assumptions will be discussed in turn.

**Important information gets more attention.** Ben Zur and Breznitz (1981) used information-boards which only allowed inspection of one piece of information at a time in their gamble-choice task. They recorded how long each piece of information was looked at, as well as the order of information use. There was a strong effect of looking time on measures of the degree to which information impacted choices. Very similar findings were reported by Payne, Bettman and Johnson (1988), who used a computer program called mouselab. In mouselab, all information is masked, and you have to move the mouse-cursor over it to inspect it.

A criticism of process tracers such as mouselab is that the effort required to obtain information, and to maintain it in memory, could interfere with the decision process (Franco-Watkins & Johnson, 2011). Eye-tracking can be argued to be a superior process tracer to both information boards and mouselab, as most sources of interference with the decision process are removed (Lohse & Johnsen, 1996). Several studies (e.g., Kim, Seligman & Kable, 2011; Fiedler & Glöckner, 2012) have confirmed findings of correspondence between attention and impact on preference using eye tracking.

**Attended information gets more important.** When decision problems are complex, or when cognitive resources are limited, decision makers often cope by relying on heuristics (Kahneman & Frederick, 2002). Heuristics are decision strategies that simplify a problem by applying simple rules to only parts of the available information (Gigerenzer & Todd, 1999). Ben Zur and Breznitz (1981) did indeed find that participants adjusted to time pressure by consulting less of the available information in their risky choice-task. In cases where parts of the information are ignored, attended information will have a stronger impact on choices.

When time pressure causes the decision maker to use heuristics, the difference in the predictions from the loss hypothesis and the focus narrowing hypothesis is simply a question of what type of heuristic the decision maker chooses to use. The loss hypothesis predicts that the decision maker will make use of the information about losses, since avoiding losses becomes more of a priority under time pressure. The focus narrowing hypothesis rather predicts that the heuristic will involve the information considered most central to performing the task, as attention is now drawn more strongly to this information.

But what about situations in which all relevant information is perceived? Can getting an increased share of attention then still cause the importance of information to increase? A growing amount of studies suggest that this may be the case. Mostly, these studies have investigated the effect of manipulating visual attention in tasks of evaluative judgments (though see also Krajbich & Rangel, 2011). The results suggest that positive evaluations become more positive and negative evaluations become more negative the larger a share of attention a stimulus is given. Shimojo, Simion, Shimojo and Scheier (2003) found this effect in judgments of face attractiveness. Armel, Beaumel and Rangel (2008) replicated the effect for evaluations of art posters and food items, including a task of choosing between aversive foods, in which increased attention caused foods to be favored less.

It is plausible, though not yet conclusively demonstrated, that this effect of attention on preferences could generalize to risky decision making. Contemplating a high probability of obtaining a gain could make you more convinced that a risk is worth taking. Thinking about how bad a large loss would be if it was to occur might sway your decision in the opposite direction.

**The present study**

In summary, results of prior studies concluding with increased reliance on loss-information under time pressure are suggested to be equally consistent with a focus narrowing interpretation, whereby the decision maker's focus narrows in on the information considered most central. Focus narrowing is also proposed to be able to account for results of prior studies that are inconsistent with the loss-hypothesis.

An increased reliance on central information under time pressure, as described by focus narrowing, has also been found in studies of riskless multi-attribute choices (Svenson & Edland, 1987). A possible causal mechanism behind focus narrowing is suggested by research on the effects of stressors on attention, combined with research on the effect of attention on decision making. Stressors such as time pressure cause attention to narrow in on the most task relevant information (Wells & Matthews, 1994). And increasing the share of attention received by information is suggested to lead to an increase in its decision weight (Krajbich & Rangel, 2011). Task relevant information will then impact choices more strongly under time pressure. In risky decision making, people vary in what kind of information they consider most task relevant (Lauriola & Levin, 2001). The impact of time pressure on risky decision making is then predicted to interact with the information preferences of the individual decision maker.

The aim of this study is to test predictions from the focus narrowing hypothesis and from the competing loss-hypothesis on the influence of time pressure on information utilization in risky decision making. Participants perform a risky decision task that incorporates all four kinds of information in risky decision making: the magnitude and probability of a potential gain is weighed against the magnitude and probability of a potential loss to determine if a gamble should be accepted or rejected. By gathering eye tracking data while participants perform multiple trials of the task, under conditions of both low- and high time pressure, it is possible to determine what information is relied on the most, and how this changes under time pressure. Mixed effects regression analyses of behavioral data are used as an additional measure of information preferences, by predicting the choices made from the magnitude- and probability-values of the gain and the loss.

The loss-hypothesis, based on conclusions drawn in prior studies, predicts that time pressure will increase reliance on information about losses, regardless of the decision maker's information preferences in the absence of time pressure. The focus narrowing-hypothesis rather predicts that the effect of time pressure will depend on how the decision maker evaluates the relative importance of the four pieces of information in the task. It predicts that time pressure will further increase reliance on the information relied on most in the absence of time pressure, and decrease reliance on the information utilized least.

# Methods

**Participants.**

25 participants (14 female) were recruited from the University of Oslo and via acquaintances to take part in the experiment. 6 participants were later excluded from analyses due to unusable eye-tracking data (3 female). All non-excluded participants had normal, uncorrected vision. Ages ranged from 20 to 45 (M = 25, SD = 6.4). All participants were briefed about the study and signed informed consent forms prior to testing. The minimum payment for taking part was 150 NOK, with the possibility of additional payment depending on task performance. All participants were tested individually. The complete session, consisting of a training phase and a main phase of the experiment, lasted for approximately 40 minutes.

**Apparatus**

The entire experimental procedure was computerized, programmed in Presentation® (Version 16.3, www.neurobs.com). Stimuli were displayed on a 19-inch Eizo Flexscan CRT monitor, with a 1280×1024 screen resolution and an 80Hz refresh rate. Subjects were seated 70 cm from the screen, with their head stabilized by chin- and forehead rests.

Gaze position data was gathered at a sampling rate of 240Hz by an iView X™ Hi-Speed monocular eye tracker, developed by SMI (Teltow, Germany). The eye tracker uses the “dark pupil technique”. Infrared light illuminates the eye, and image processing software calculates gaze position based on the location of the pupil and the reflection of infrared light on the cornea, as captured with an infrared camera. Only the left eye was tracked.

**Design**

**Gambling task.** In a within-subject design, participants performed a computerized risky decision making task under conditions of both high- and low time pressure (2000ms- and 15000ms time limits). On each trial, participants chose whether to accept or reject a mixed outcome gamble displayed on screen. Each gamble consisted of four pieces of information: the magnitude of a potential gain (GM), the magnitude of a potential loss (LM), the probability of the gain (GP) and the probability of the loss (LP). If the gamble was accepted, there was a GP probability of receiving a gain of GM and an LP probability of losing LM. It was possible for both the gain and the loss to occur on the same trial, yielding a pay-out equal to the sum of the gain and the loss. It was also possible for neither to occur, yielding a pay-out of zero. If the gamble was rejected, the pay-out was always zero for that trial. If no response was given within the time limit, the response was automatically set to "accept" if the pay-out from the gamble was negative, and "reject" if the pay-out was positive. The sets of possible values for each type of information were:

GM: [30, 60, 120]

LM: [-30, -60, -120]

GP: [.2, .4, .8]

LP: [.2, .4, .8]

All 81 permutations of these values were presented a total of 4 times each, twice under high time pressure and twice under low pressure, for a total 324 trials. The expected values (EV) of gambles ranged from -90 to 90, symmetrically distributed around zero (19 out of the 81 different gambles had an EV of zero). The order of trials was randomized, with the constraint that time pressure was manipulated in alternating blocks of 81 trials. Whether the first of the four blocks was high- or low pressure was counterbalanced across subjects. To keep task motivation high throughout testing, subjects were paid the sum of pay-outs from 10 randomly selected trials, given that this sum was positive.

The sets of values for the information dimensions were chosen to ensure that there were no a priori reasons to focus more on some dimensions than others across trials. All four sets have one favorable value (highest values for gain-dimensions, lowest absolute values for loss-dimensions), one unfavorable value (low gains and high losses), and one neutral value. All values vary independently of each other, with values within sets having equal probabilities of occurring on each trial. Magnitudes are matched for absolute values, and all four sets have the same ratios of their values (i.e. [1, 2, 4]).

This means that to a decision maker who is *risk neutral and who only cares about the expected value of gambles*, the favorable values of the different dimensions are all equally favorable, the unfavorable values are equally unfavorable, and the neutral values are all equally neutral. If this decision maker was to choose which dimensions to rely on in a heuristic approach to maximize his pay-outs (i.e. only using three, two or one dimension(s), instead of integrating all four), he would be indifferent as to which dimensions to include and exclude in his heuristic. All heuristics that exclude a single cue lead to the same reduction in pay-out, regardless of which cue is ignored. The same is true when two or three cues are excluded. And in resolving tie-situations, where there are equal amounts of favorable and unfavorable values, it would be of no consequence to the risk neutral decision maker which dimensions had the favorable and unfavorable values.

Any tendencies for subjects to prefer relying on some dimensions over others are then more readily interpretable as reflecting general information preferences, rather than being artifacts specific to the current task. A probable source of deviations from equal reliance on all dimensions is a subject’s risk preferences. While the selection of what dimensions to use in a heuristic, or the selection of what dimension to place extra weight on in tie-situations, is irrelevant to the average expected pay-off from accepted gambles, it has a marked influence on how risky the accepted gambles will tend to be. Specifically, a focus on keeping the probabilities and magnitudes of losses low will lead to substantially less variability in pay-offs than will a focus on maximizing the probabilities and magnitudes of gains. Risk averse subjects are then likely to rely more on loss information, while risk seeking subjects would tend to rely on gains. As to the question of whether to rely more on probability or magnitude information, risk preferences are less of a factor. Any significant tendencies to prefer one over the other would here be more likely to reflect some other aspect of the decision making process, rather than risk preferences.

The time-limits in the two time pressure conditions (2000ms in low pressure and 15000ms in high pressure) were set on the basis of results from pre-testing. As a time constraint only represents time pressure if it interferes with task performance, it was important that there was a decline in performance from low to high pressure. The percentage of answers made in accordance with EV on trials with non-zero EV gambles (“accept” when EV of the gamble is positive, “reject” when negative) works as a crude measure of performance in risky choice tasks. It was found that a 2000ms time limit produced a suitably large drop in performance, from a mean accuracy of about 85 % in low pressure to about 74 % in high pressure. As response times only very rarely were above 10000ms when no time limit was given, it was set to 15000ms in the low pressure condition.

Time pressure was manipulated in blocks of 81 trials, for a total of two blocks of each time pressure condition. Varying time pressure in large blocks allowed participants time to adjust their strategy to fit the time constraint. Pre-testing with shorter blocks (e.g. 6 trials) produced much smaller differences in response times and accuracies between conditions than what is found for larger blocks.

***Implementation.*** As an additional measure to keep a priori differences of information-dimensions to a minimum, the values of each of the dimensions were represented by line-cues rather than by numbers on screen (see Figure 1).  All four cues were equally luminant, as they were composed of the same amounts of white pixels (RGB = 255, 255, 255). They subtended

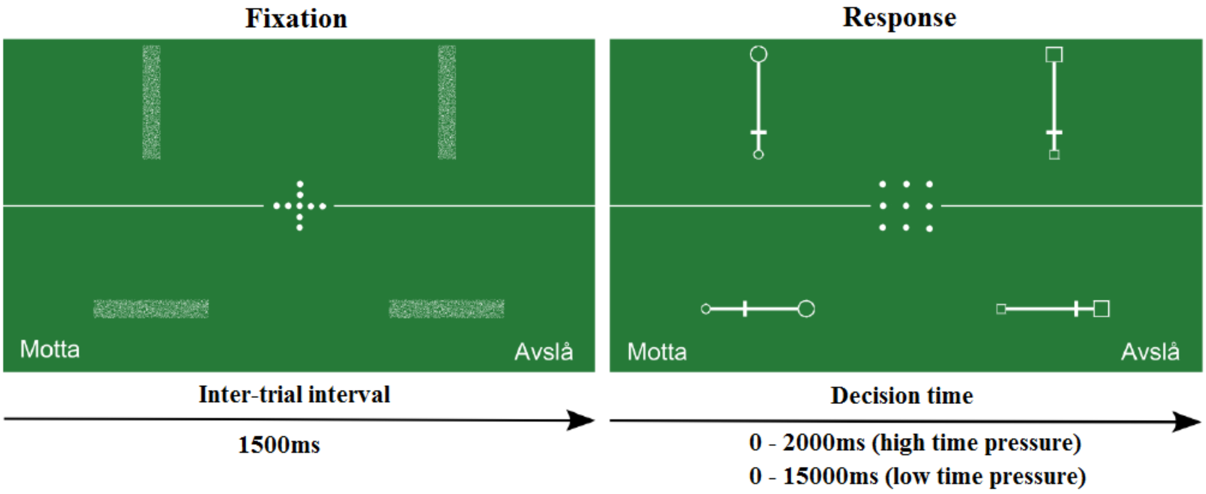


*Figure 1.* The gamble task. The four line-cues indicate the properties of a gamble, which subjects decide whether to accept or reject. "Motta" and "Avslå", Norwegian for "accept" and "reject", is written in the lower corners to indicate which button to press for the desired action (whether "accept" was right or left was counterbalanced across subjects). The time-limit to respond is indicated by the background color: 2000ms in the high pressure condition and 15000ms in the low pressure condition. There is a 1500ms inter-trial interval, in which line-cues are masked.

4.1° of visual angle in length (160 pixels) and 0.7° in width (28 pixels). They all consisted of a line with unequally sized geometrical shapes on the endpoints. Whether the cue was a magnitude- or a probability cue was communicated by whether the shapes were circles or squares (which shape symbolized which cue-type was counterbalanced across subjects). Whether a cue was associated with a gain or a loss was communicated by whether the line was vertical or horizontal (also counterbalanced). The value of a cue on a trial was indicated by a small bar crossing the line; the closer this bar was to the larger of the two geometrical shapes, the greater the (absolute) value of the cue.

The cues were placed towards separate corners of the screen, with each cue being moved 5.6° (220 pixels) either left or right from the center of screen, and 5.1° (200 pixels) either up or down. Which cue was placed towards which corner was constant throughout the trials of a single participant, but it was counterbalanced across participants. The constraints on the counterbalancing of cue-positions were that the two gain cues were always placed towards the same bottom- or top edge of the screen (with losses towards the opposite edge), and that the probability-cues were always on the same left- or right edge of screen (with magnitudes on the opposite side). A horizontal line across the screen separated the gain- and loss-cues.

The time limit to respond was indicated by the background color, which was either blue (RGB = 48, 81, 156) or green (RGB = 38, 122, 56). The colors were matched for luminance. Which color represented which condition was counterbalanced across participants.

Trials were separated by an inter-trial interval of 1500ms, in which participants were instructed to fixate on the center of a nine-dot fixation cross, 3.2° in length and width (125 pixels). The start of a trial was indicated by the fixation cross turning into a quadratic figure composed of the same nine white dots, with the same length and width.

**Procedure**

Prior to testing, participants received a quick briefing on the experiment, and they signed forms to indicate their consent. Testing took place in a windowless room, under conditions of normal indoor lighting.

In order for participants to reach a stable level of proficiency on the task before the main phase of the experiment, they completed a training phase. They were first introduced to the rules of the task, and the payment-system, through both verbal and written instruction. They were then shown a screen with all the different line-cues together with the values they represented. They were encouraged to spend some time to memorize and understand the logic of the cues, and they were told that reminders would appear throughout the training phase. After that, they completed 10 minutes of practice trials. The practice trials were identical to the experimental trials, except that there was no time-limit (the session ended after 10 minutes regardless of the number of trials completed). Additionally, the outcome of the gambles was displayed after every trial. The screen associating the line-cues with values was shown every 27th trial. Participants were also shown the accumulated pay-outs from the last 27 trials, as a measure of performance. Even though no eye tracking took place in the training phase, participants still used the chin- and forehead rests, to get used to keeping their head movements to a minimum. They were also instructed to fixate on the fixation cross between trials.

After the training phase, participants were given the opportunity to take a short break, and to ask questions if they were still unsure about aspects of the task. To acquaint participants with the time pressure manipulation and to ensure that the task had been understood correctly, an additional 20 practice trials were completed, this time with time pressure (10 low pressure trials and 10 high pressure trials, in blocks of 5).

The eye tracker was then calibrated. Participants were asked to sequentially fixate on several points on a 3 × 3 fixation map (1280 × 1024 pixels). The eye tracking software continuously adjusts its estimated gaze-locations by comparing its estimates to the coordinates of the points at which the participant is instructed to fixate. After calibration, participants were again reminded to keep their heads as still as possible throughout testing and to fixate on the fixation cross between trials, before the main trials were initiated.

In the main trials of the task, no single-trial feedback was given. However, on every 27th trial participants were still informed of the accumulated pay-outs from the previous 27 trials. Pre-testing had shown that this was an effective measure to keep task performance at a high level throughout. Prior to each 81-trial time pressure block, a screen informed participants about what time pressure condition was coming next. On average, participants used 18.2 minutes (SD = 2.3) to complete all 324 trials, with an average duration of low pressure blocks at 5.6 minutes (SD = 1.0) and an average duration of high pressure blocks at 3.5 minutes (SD = 0.8).

## Analyses

**Two separate measures of information reliance.** To investigate how much participants rely on each of the four information-cues to make choices, two separate sets of data are analyzed: eye tracking data and choice-data. Eye tracking data will be used to assess visual attention for different cues. The assumption is that the more prominently a cue features in the decision making process, the more visual attention that cue will be given. With the choice data, cues are compared on how well their values predict accept/reject responses. The more important a cue is to a participant, the more likely that participant will be to accept when the cue has a beneficial value and to reject when the cue has a disadvantageous value.

Having two separate measures of cue reliance helps verify the validity of both measures. The larger the extent to which they show similar results, the more confidence can be had in both their validities as measures of cue reliance. The correspondence between the two measures will be investigated through correlations, and through a regression analysis.

Additionally, the measures have different strengths and weaknesses, so to some extent they make up for each other's shortcomings. Eye tracking has the advantage of providing trial-by-trial data. Analyses of choice data can only produce estimates of cue-reliance for a set of trials, as it is impossible to tell what information a single response was based on. As the focus narrowing effect is presumed to depend on attention, eye tracking is also valuable in that it measures attention more directly than the analyses of choices do.

The main weakness of eye tracking as a measure of cue-reliance is its strong dependence on the assumption that a decision maker's degree of reliance on a cue is reflected in the amount of visual attention (i.e. dwell time) that cue is given. As discussed in the introduction, there is some empirical support for this assumption (e.g., Kim, Seligman & Kable, 2012). Still, it is felt premature to put so much trust in this assumption as to not include an additional measure of cue reliance that is not dependent on it.

**Mixed effects regression analysis.** Both the eye tracker data and the choice-data in this experiment are analyzed using mixed effects regression analysis (also known as multilevel modeling, hierarchical regression, mixed modeling, as well as other names), with the R-package *lme4* (Bates, Maechler, Bolker & Walker, 2014). Mixed effects regression is used for analyzing hierarchically structured data, in which observations are nested within higher level groups (Hox, 2002; Gelman, 2006). Such as when students are nested within classes, or when employees are nested within firms. In the present experiment, the observations of attention and choices on each trial are nested within subjects. Subjects are likely to differ systematically in how much they attend to the different cues, and in how much importance they attach to the values of the different cues in making choices. This leads to a violation of the assumption made by many common analytical techniques that observations are sampled independently of each other. Mixed effects regression can account for these systematic differences between subjects by estimating subject-specific random effect-coefficients for the intercept and/or the slopes of the predictors in the regression equation. These random effects are added to the overall fixed effect-coefficients, which represent the average coefficients across subjects, to allow the predictions of the regression equation to depend on what subject the predictions are made for. The general form of a simple mixed effects regression, with a two-tiered hierarchy and a single predictor, can be expressed as follows (adopting notation from Hox (2002)):

$$Outcome_{ij} = (\gamma_0 + u_{0j}) + (\gamma_1 + u_{1j})Predictor_{ij} + r_{ij}$$

$i$ represents the lowest level of the hierarchy, which is the single trial-level in this context. $j$ represents the tier above the trial-level in the hierarchy, the subject-level. $r_{ij}$ is the error term. $\gamma_0$ and $\gamma_1$ are the fixed effects, representing the average intercept and the average slope across all subjects, respectively. $u_{0j}$ and $u_{1j}$ are the random effects for the intercept and the slope, representing how much subject $j$'s intercept and slope deviate from the group-average.

Having separate random effect-coefficients for each subject is vital for the purposes of this study. The focus narrowing hypothesis predicts that the effect of time pressure on a subject's reliance on an information-cue depends on how much the subject relies on that cue in the absence of time pressure. Subject-specific cue-reliance scores, as are provided by random effect-coefficients, are thus essential. They allows testing the prediction that cue-reliance scores above the average in low pressure will increase further under time pressure, and that cue-reliance below average will decrease. The regression models used for specific analyses are described together with the results.

**Pre-processing of eye tracking data.** Participants were excluded from the experiment if more than 30 percent of their gaze-data was missing (3 participants), or if the data were deemed unusable based on visual inspection (3 participants).

Detection of eye-blinks and subsequent interpolation of missing data is done using the R-package *zoo* (Zeileis, Grothendieck & Zeileis, 2007). As eye-blinks normally last between 100-400ms (Holmqvist et al., 2011), stretches of missing data shorter than 400ms (96 samples at a frequency of 240 Hz) are defined as blinks. The five samples before and after a blink are then removed, as these are typically corrupted by the blink (Holmqvist et al.). Linear interpolation is then performed to replace gaze-coordinates that are missing due to eye-blinks.

To correct for drift in the eye tracking data, the mean x- and y coordinates for the fixation locations in the last 500ms of the inter-trial interval are compared to the coordinates for the center of the fixation point on screen. Participants had been instructed to fixate on the fixation cross throughout the inter-trial interval. For each block of 81 trials, if mean gaze-coordinates deviated by more than 1.6° of visual angle (80 pixels) from those of the center of the fixation cross, adjustments are made according to the size of the deviation.

Areas of interest (AOI) for the eye tracking analyses are defined as squares around each information-cue, 360 pixels in length and width.

**The dependent variable in eye tracking analyses.** The dependent variable in the analysis of cue-reliance has to be an expression of how much a cue was attended to relative to the other cues. It is therefore necessary that it expresses *a proportion* of some measure of attention, rather than an amount or an average. If, for example, the dependent variable had been the total amount of time spent attending to a cue on a trial (or the amount of fixations, or the average duration of fixations), then you would also need the measurements from the other cues to make inferences about the reliance on a cue. 1000ms spent attending to a cue signifies stronger reliance if all other cues received only 500ms than if they received 2000ms.

The proportion of the total decision time- or of the total amount of fixations directed at a cue is also uninformative. Reliance then depends on how large a proportion of the time/fixations that was not directed at any of the cues. The remaining options are then the proportion of *the time spent attending to cues* that was spent on a particular cue, and the proportion of *the fixations directed at cues* that were directed at a particular cue. Out of these two, the proportion of fixations can be slightly misleading in the high pressure condition, where cues often receive only a single fixation. So the dependent variable chosen is the proportion of the time spent attending to cues on a trial that was spent attending to a particular cue. This variable will be referred to as “SoA”, for “Share of Attention”.

Mixed effects regression analyses will investigate the distribution of attention between cues, and how this changes under time pressure, by predicting SoA from what cue-type the measurement originates from, and the time pressure condition. Model comparisons and contrasts between estimated coefficients will be used to explore matters further.

**Analyzing the use of decision strategies.** The distribution of SoA on a trial is indicative of whether the participant used a heuristic strategy of only using parts of the information, or if the value of all cues was integrated in the decision. The larger the extent to which choices are simplified by the decision maker, the more unequal the distribution of attention between cues will tend to be. To analyze the extent to which participants rely on heuristic strategies to make their choices, and how this changes under time pressure, a Gini-coefficient (Gini, 1921) is calculated for the distributions of visual attention on every trial. The Gini coefficient is a measure of inequality, typically used for the distribution of wealth in countries. It takes values between 0 and 1, with zero expressing complete equality (all cues get equal fixation time) and 1 expressing complete inequality (a single cue gets all the fixation time). A mixed effects regression model is fitted, where the value of the Gini coefficient on a trial is predicted from the time pressure condition of that trial

The prediction, which is in line with both the focus narrowing hypothesis and with research on heuristics, is that the Gini will be higher under time pressure. A focus narrowing-effect, where attention narrows in on the most important information, would produce a higher average Gini-coefficient under time pressure. Similarly, findings that people tend to cope with restrictions on their cognitive resources by relying more on heuristics (e.g., Gigerenzer & Todd, 1999) also imply that Gini will be higher under time pressure.

**The dependent variable in analyses of behavioral data.** The approach to estimating information preferences from choices is explained more fully in the Regression models & Results-section. In brief, the logic is as follows: As a first step, a logistic mixed effects regression model is fitted. The model estimates how well responses are predicted by the values of the different cues, in each time pressure condition. How a single subject evaluates the relative importance of the cues in a given time pressure condition can be judged from the relative size of the coefficients estimated by the model. The relative size is used as the dependent variable, because the absolute size of coefficients also depends on how accurate the subject is in how he uses the cue-values (i.e. his decision accuracy). The more random error there is in decisions, the less accurate predictors of responses the cue-values will be. This leads to the problem that cue-reliance scores cannot be compared across subjects or time pressure conditions, since accuracies will tend to differ. By expressing the four coefficients from the same subject and time condition as a proportion of their sum, only their relative size is communicated. This means that they become pure measures of cue-reliance. These scores will be referred to as SoD, for Share of Decision weight. The SoD-scores will then be the dependent variable in further analyses of information preferences, similar to analyses done using SoA.

# Regression Models & Results

All analyses were done in the statistical software environment R (R Core Team, 2012).

**Preliminary analyses**

**Training phase.** In investigating whether all participants had properly learned the task before the main phase of the experiment, the measure of decision accuracy was the proportion of responses that were made in accordance with the expected value (EV) of the gambles. This means choosing “reject” when EV is negative and “accept” when EV is positive (zero-EV gambles are disregarded here). The correspondence of responses with EV can only be considered an approximation of accuracy on risky choice tasks. If a person prefers rejecting a gamble with a slightly positive EV because of fear that it might yield a loss, that preference is not “wrong”. But since these preferences are not easily measured without making a number of assumptions (e.g. about the form of utility or probability weighting functions), the simplifying assumption that subjects generally prefer choosing in accordance with EV is made. The proportion of EV-accordant responses in training ranged between .67 and .95. Number of trials completed within the ten minutes the training lasted ranged from 40 to 160. Binomial tests were done on all subjects to determine if their probability of making the highest EV choice differed from chance. All nineteen subjects passed this test (highest p-value = 0.02).

**Manipulation check for time pressure.** Time pressure was manipulated by changing the time limit for responding (15 s in low pressure, 2 s in high pressure). As per Maule and Hockey (1993), a time limit needs to interfere with both the time taken to make a choice and the quality of choices made before it can be said to represent time pressure. Response times were significantly faster in the high pressure condition (M = 1147ms, SD = 205ms) than in the low pressure condition (M = 2643ms, SD = 995ms) as compared using a paired samples *t*-test; $t(18) = -6.65$, $p < .001$. Accuracy was also significantly reduced under high pressure (M = .86, SD = .06) compared to low pressure (M = .77, SD = .07); $t(18) = -7.96$, $p < .001$. All participants had lower mean response times and mean accuracies under high time pressure. The proportion of high pressure trials where no response was given within the time limit was 0.03 (ranging from 0.0 to 0.11 between participants). In the low pressure condition, all responses except two were given in time.

## Eye tracking

**Predicting SoA from cue-type and time pressure.** To analyze how attention is distributed between information-cues, and how this distribution changes under time pressure, the following mixed effects regression model was fitted:

$$\boldsymbol{SoA_{ij}} = -1 + (\gamma_1 + u_{1j})\boldsymbol{GMt0_{ij}} + (\gamma_2 + u_{2j})\boldsymbol{GPt0_{ij}} + (\gamma_3 + u_{3j})\boldsymbol{LMt0_{ij}} + (\gamma_4 + u_{4j})\boldsymbol{LPt0_{ij}} + (\gamma_5 + u_{5j})\boldsymbol{GMt1_{ij}} + (\gamma_6 + u_{6j})\boldsymbol{GPt1_{ij}} + (\gamma_7 + u_{7j})\boldsymbol{LMt1_{ij}} + (\gamma_8 + u_{8j})\boldsymbol{LPt1_{ij}} + r_{ij}$$

(The model is named *SoA* = *Cue* × *Time* in Table 2, which contains key statistics for all regression models in this thesis.) In the model, SoA for an AOI is predicted from what cue that AOI is associated with, and what time pressure condition the measurement originates from. The predictors are all dummy variables. The pairs of capitalized letters – “GM”, “GP”, “LM” and “LP” – represent the different cues. G is for “gain”, L is for “loss”, M is for “magnitude” and P is for “probability”. “t0” and “t1” specify the time pressure condition: t0 is low pressure and t1 is high pressure. So if, for example, a measurement of SoA is from an AOI of the loss magnitude cue in the high time pressure condition, then the predictor LMt1 is coded as 1, and all other predictors are 0. Otherwise, LMt1 is 0 and another predictor is 1.

The expected SoA for a cue if all cues are equally important to the decision maker is 0.25. As it is more interesting to investigate how SoA deviates from this expected value than how it deviates from zero, SoA is centered on 0.25 in this analysis.

In addition to fixed effects coefficients, represented by $\gamma$’s, the regression generates subject-specific random effect coefficients for all predictors, which are represented by $u$’s in the equation. $\gamma$-coefficients signify the average SoA for the specified cue in the specified time pressure condition. $u$-coefficients show how much a particular subject’s average SoA for a predictor differs from the group-average.

The model is fitted without an intercept, as indicated by the “-1” in the equation. This enables testing whether each coefficient differs significantly from zero (indicating an SoA of 0.25), rather than testing the difference from the coefficient chosen as the intercept. And it also facilitates contrasts, where sets of coefficients are compared (discussed further on).

Table 1.

*Fixed effects for model predicting SoA*

| **Predictor** | **γ + .25** | **SE** | ***t(20)*** |
|---|---|---|---|
| *GMt0* | .239 | .019 | -0.61 |
| *GPt0* | .323 | .019 | 3.88*** |
| *LMt0* | .183 | .017 | -3.83** |
| *LPt0* | .255 | .026 | 0.21 |
| *GMt1* | .204 | .030 | -1.53 |
| *GPt1* | .382 | .032 | 4.08*** |
| *LMt1* | .160 | .025 | -3.54** |
| *LPt1* | .254 | .035 | 0.11 |

Fixed effects, $\gamma$, for each predictor in the model. Adding .25 to $\gamma$ adjusts for the centering of SoA on .25. SE is the standard error of $\gamma$. *t* is the *t*-value, testing whether SoA differs from 0.25. **p<0.01, ***p<0.001.

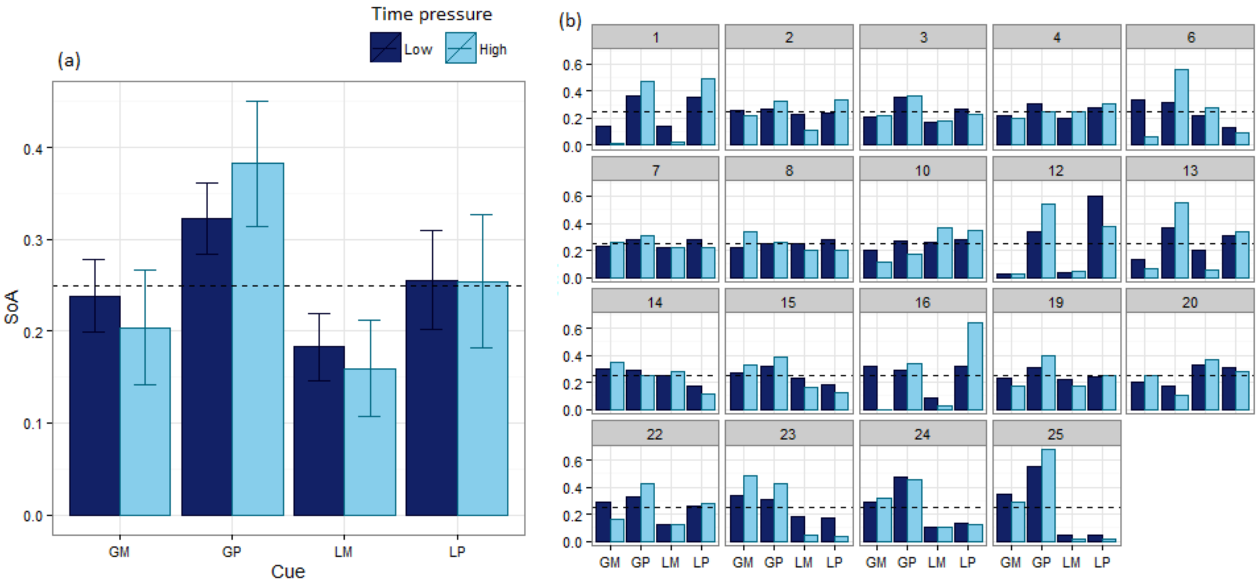


*Figure 2.* Coefficients from the model predicting SoA. (a) Plot of the fixed effect coefficients, representing the average SoAs across subjects for each combination of cue and time pressure, with error bars representing a 95 % CI. Dark blue is for low time pressure, light blue is for high pressure. The coefficients in are adjusted for the centering of SoA on its average of 0.25, with dotted lines in the plots representing an SoA of 0.25. (b) Plots of the average SoAs for each subject separately (i.e. sums of fixed effect- and random effect coefficients).

The results showed that there was a pronounced tendency for participants to attend the most to the gain probability cue, in both time pressure conditions (see Table 1 and Figure 2). Averaged across subjects, GP was fixated 32.3 % of the time under low time pressure, and 38.2 % of the time under high pressure. The cue given the least attention was LM, with an SoA of .183 in low pressure and .16 in high pressure. GP and LM were the only cues with average SoAs significantly different from .25.

***Exploring the distribution of attention.*** $R^2$, the proportion of variance in the outcome variable that is explained by a model, is not easily defined for mixed effects models. There is variance associated with each random effect in addition to the residual variance, so it is not clear what variance to use when computing $R^2$ (Snijders & Bosker, 1994). The ability of a model to account for the data must therefore be assessed in alternative ways, such as through comparisons with other models.

To establish that the distribution of attention between cues is different from an even distribution (i.e. that the model has explanatory relevance), the regression model is compared to an empty model predicting SoA with only an intercept (named *SoA = Empty* in Table X). As denominator degrees of freedom for *F*-tests are not easily defined in model comparisons involving mixed effects models, likelihood ratio tests will be used.

The full model provided a significantly better fit to the data than the empty model ($\chi^2(42) = 12660$, $p < .001$). The *p*-value of this comparison communicates the same information as the *p*-value of $R^2$ in ordinary regression; the probability of data at least as extreme as those observed, given that the predictors are actually unrelated to the outcome variable.

In analyzing *how* the distribution of attention differed from an even distribution, contrasts were carried out to see if there were main effects of valence (gains vs losses) and dimension (probabilities vs magnitudes). Gain-cues were contrasted with loss-cues and probability-cues where contrasted with magnitude-cues:

$$\boldsymbol{SoA}_{ij} = -1 + (\gamma_1 + u_{1j})\boldsymbol{GvsL}_{ij} + (\gamma_2 + u_{2j})\boldsymbol{PvsM}_{ij} + r_{ij}$$

(The model is called *SoA = GvsL + PvsM* in Table 2.) The $\boldsymbol{GvsL}_{ij}$-predictor takes the value 1 for SoA-scores associated with gain-cues, and the value -1 for SoAs associated loss-cues. $\boldsymbol{PvsM}_{ij}$ is 1 for all probability cue-SoAs and -1 for all magnitude cue-SoAs. Positive coefficients for the predictors indicate that the cues coded with 1 on average get higher SoA-scores than the cues coded with -1. And, vice versa, negative coefficients indicate that cues coded with -1 are attended more.

Information about gains was attended significantly more than information about losses ($\gamma_1 = .036$, $t(20) = 2.35$, $p < 0.05$), and probability-information was attended significantly more than magnitude-information ($\gamma_2 = .054$, $t(20) = 3.42$, $p < 0.01$).

***The effect of time pressure.*** To test whether distributions of attention differed between time pressure conditions, the full model was compared to a simpler model predicting SoA from cue-type only, without making separate predictions for the two time pressure conditions (*SoA = Cue* in Table 2). Again, the full model was found to provide a significantly better fit ($\chi^2(30) = 2456.1$, $p < .001$).

The focus narrowing-hypothesis proposes that information-preferences are amplified under time pressure. The cues relied on the most in low pressure are relied on even more under high pressure, and the cues relied on the least are relied on even less. The predictions made for the fixed effects of the SoA-model are then that the GP-cue, which had an SoA significantly above average in low pressure, will be attended even more under high pressure, and that the LM-cue, which was significantly below average in low pressure, will be attended even less. Contrasts are carried out to test these predictions:

$$\boldsymbol{SoA}_{ij} = -1 + (\gamma_1 + u_{1j})\boldsymbol{GP\_inc}_{ij} + (\gamma_2 + u_{2j})\boldsymbol{LM\_dec}_{ij} + r_{ij}$$

(See *SoA = GP_inc + LM_dec* in Table 2.) $\boldsymbol{GP\_inc}_{ij}$ is a dummy-variable testing whether gain probabilities receive even more attention under high- than low pressure. It is coded as 1 for SoAs from GP in high pressure and -1 for GP in low pressure. All other conditions are coded as 0. ***LM_dec***$_{ij}$, testing whether attention to loss magnitudes decreases under time pressure, is coded as 1 for LM in low pressure and -1 for LM in high pressure, and otherwise 0.

*T*-tests of whether the coefficients where higher than zero showed that GP indeed was attended a significantly larger proportion of the time under high pressure than under low pressure ($\gamma_1 = .028$, $t(20) = 2.77$, $p < 0.01$), but that the decrease in attention to LM was not significant ($\gamma_2 = .010$, $t(20) = 1.30$, $p = 0.10$).

**Predicting the Gini-coefficient from time pressure.** Both the focus narrowing hypothesis and research on when people increase their reliance on heuristics (e.g., Gigerenzer & Todd, 1999) imply that attention will be less evenly distributed under time pressure. The SoA-plots are suggestive of such an effect. But to properly examine how the distribution of attention changes under time pressure, the following mixed effects model is fitted:

$$\boldsymbol{Gini}_{ij} = (\gamma_0 + u_{0j}) + (\gamma_1 + u_{1j})\boldsymbol{time}_{ij} + r_{ij}$$

(See *Gini = Time* in Table 2.) The value of the Gini coefficient on a trial (***Gini***$_{ij}$), expressing the inequality of the distribution of attention, is predicted from the time pressure condition of that trial (***time***$_{ij}$). ***time***$_{ij}$ is coded as 0 for low time pressure and 1 for high pressure, meaning that the fixed effect for the intercept ($\gamma_0$) represents the average Gini coefficient in low pressure and the fixed effect for the slope ($\gamma_1$) represents how the Gini coefficient changes under time pressure. In addition to the fixed effects, random effect coefficients are estimated for both the intercept and slope for each subject ($u_{0j}$ and $u_{1j}$).

The Gini coefficient increased from an average of .29 for low pressure trials ($\gamma_0 = .29$, $t(19) = 10.9$, $p < .001$) to .41 for high pressure trials ($\gamma_1 = .13$, $t(19) = 6.9$, $p < .001$). The average distribution of SoA on a single low pressure trial, from most to least attended, was [0.44, 0.28, 0.17, 0.10]. Under high time pressure, the average distribution of SoA-scores was [0.55, 0.30, 0.12, 0.05]. There was considerable variability in how evenly participants distributed their attention, as illustrated by Figure 3. Some attended

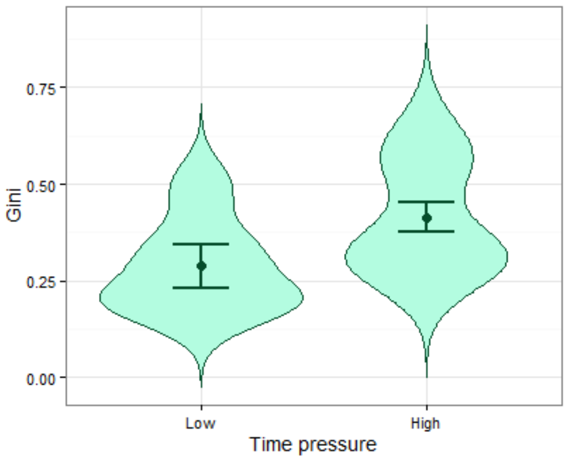


*Figure 3.* Density plots, showing how Gini-scores vary between subjects in the two time pressure conditions. Points indicate the mean Gini for each condition, with error bars indicating a 95% CI.

quite equally to all cues even under high pressure, while others seemed to rely on heuristics even under low pressure.

**Summary of eye tracking results.** Results from group-level analyses of eye tracker data indicate that participants generally preferred attending to gains over losses and to probabilities over magnitudes. In line with focus narrowing, these tendencies were intensified under time pressure. Additionally, participants tended to rely on a smaller subset of the available information under time pressure, as indicated by the Gini-analysis.

We now turn to group-level analyses of cue-reliance based on behavioral data, to explore the extent to which eye tracking results are replicated. After that, the focus narrowing hypothesis is tested more directly, through an analysis of the effect of time pressure on subject-level cue-reliance scores.

## Behavioral analyses

**Logistic regression predicting choices.** As a first step to estimating how much participants rely on the different cues from data on what choices they made, a logistic mixed effects regression analysis is run. The probability of accepting a gamble is predicted from the values of the different cues on that trial, with added interactions for how the influence of cue-values depends on the time pressure-condition:

$$\boldsymbol{ln}\left(\frac{\boldsymbol{p(accept)}}{\boldsymbol{p(reject)}}\right)_{\boldsymbol{ij}} = (\gamma_0 + u_{0j}) + (\gamma_1 + u_{1j})\boldsymbol{zGM_{ij}} + (\gamma_2 + u_{2j})\boldsymbol{zGP_{ij}} + (\gamma_3 + u_{3j})\boldsymbol{|zLM|_{ij}} + (\gamma_4 + u_{4j})\boldsymbol{zLP_{ij}} + (\gamma_5 + u_{5j})\boldsymbol{time_{ij}} + (\gamma_6 + u_{6j})\boldsymbol{zGM_{ij}}\times\boldsymbol{time_{ij}} + (\gamma_7 + u_{7j})\boldsymbol{zGP_{ij}}\times\boldsymbol{time_{ij}} + (\gamma_8 + u_{8j})\boldsymbol{|zLM|_{ij}}\times\boldsymbol{time_{ij}} + (\gamma_9 + u_{9j})\boldsymbol{zLP_{ij}}\times\boldsymbol{time_{ij}} + r_{ij}$$

(See *P(accept) = CueVal × Time* in Table 2.) The dependent variable is the probability of accepting a gamble, expressed as the natural logarithm of the odds-ratio of choosing "accept". The intercept ($\gamma_0$) represents the probability of accepting when all predictors are at zero, i.e. the general bias towards accepting or rejecting gambles. $time_{ij}$ is a dummy-variable specifying the time pressure condition, coded as 0 for low pressure and 1 for high pressure. The coefficient for $time_{ij}$ ($\gamma_5$) then shows how the intercept changes from low- to high time pressure. $zGM_{ij}$, $zGP_{ij}$, $|zLM|_{ij}$ and $zGM_{ij}$ are the z-standardized cue-values on a trial (gain magnitude, gain probability, loss magnitude and loss probability, respectively). The loss magnitude cue is given absolute values prior to z-standardization, to capture how a large loss should pull a rational decision maker's willingness to accept a gamble down rather than up. Coefficients generated for these predictors indicate how the cue-values influence the predicted response. Coefficients for the interactions between cue-values and time pressure represent how a cue's ability to predict responses changes under time pressure. The model generates fixed effect coefficients for each predictor and the intercept (the $\gamma$'s), and it also generates random effect coefficients for each predictor and the intercept for all subjects (the $u$'s).

As the values are z-standardized, responses are predicted from how many standard deviations a particular cue-value differs from the mean value of that cue. The set of values for all four cues is then the same, [-1.07, -0.27, 1.34], since the original values of the cues were equally large in proportion to each other, with each value appearing equally often. Z-standardizing allows inferring the relative decision weight of each cue by directly comparing the size of the coefficients produced by the model (though only if comparing coefficients from the same subject and time pressure condition, as will be discussed further on). The more strongly a cue is relied on to make choices, the better a predictor its z-value will be of the responses given and the larger the regression coefficient will be. If someone cares strongly about gain magnitude, for instance, he/she will be likely to accept a gamble when the gain magnitude is high, and to reject a gamble if the gain magnitude is low. The gain magnitude will then be a good predictor of the response made, and it will get a larger regression coefficient than the cues that are relied on less. If the predictors were the actual cue-values instead of the z-standardized values, magnitude-cues would get small coefficients compared to the probability-cues even when magnitudes are relied on strongly, since the magnitude-values are larger than the probability-values.

As the cue-values vary independently of each other, and as all possible combinations of cue values appear exactly twice under low pressure and twice under high pressure, the predictors are completely uncorrelated for both the high- and low time pressure conditions (with minor exceptions created through the infrequent non-response trials). Notably, as most other studies have used tasks were gain- and loss probabilities are perfectly negatively correlated (GP equals 1-LP on every trial), this kind of analysis of information-reliance is typically made impossible for probability-information.

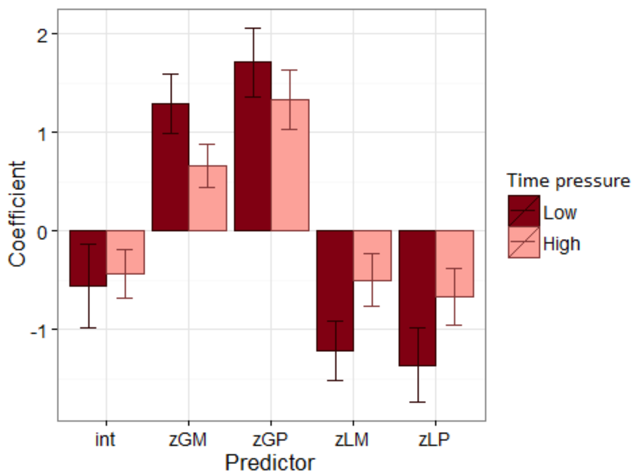


*Figure 4.* Fixed effect coefficients for the logistic regression predicting the probability of accepting a gamble from the values of the cues. Error bars indicate 95% CI.

***The coefficients generated, and why they need to be adjusted.*** The results of the analysis predicting responses from cue-values (see Figure 4) show that cues generally get less predictive of the response under time pressure; all fixed effect-coefficients get significantly closer to zero. Most subject-level coefficients (fixed effects plus random effects) get smaller under time pressure as well (see Figure 5a).

This is related to how time pressure caused a decrease in decision-accuracy. Assuming that time pressured participants are not willfully making their responses less accordant with the EV of gambles, a decrease in decision accuracy can be described as an increase in decision-randomness. The more random error there is in the decision process, the less predictable responses will be from the values of the cues. (More technically, modeling of more random choices results in higher likelihood if less certain predictions, i.e. choice probabilities distant from 0 or 1, are made. In logistic regression models, regression weights reflect both the importance of a cue and the certainty of prediction, and less certain predictions are achieved through smaller regression weights.)

In summary, for a set of four subject-level coefficients from the same subject and the same time pressure condition, the relative size of coefficients is determined by how much the subject relies on each cue, while the absolute size of a coefficient is also influenced by the accuracy of the subject in that time pressure condition. This means that subject-specific random effect coefficients cannot be compared between subjects with different decision accuracies. It will not be clear how much of the difference in the size of coefficients is due to differences in cue-reliance and how much is due to differences in accuracy. Similarly, coefficients cannot be compared across time pressure conditions, since accuracy is likely to differ between the conditions. Only comparisons between coefficients from the same participant and within the same time pressure condition are interpretable as pure comparisons of cue-reliance.

***How the coefficients are adjusted.*** To deal with the problem described above, new cue-reliance scores are calculated for each subject, by performing two operations on the subject-level coefficients from the regression (see Figure 5). Firstly, to make scores more easily comparable to the SoA-scores from the analyses of eye tracker data, the coefficients for the two kinds of loss cues are multiplied by -1. This way, all cue-reliance scores are positive (except for a very slightly negative LM-score from subject 22, who seemingly ignored the LM-cue in the high time pressure condition).

Secondly, to remove the influence of accuracy on cue-reliance scores, and also to further increase comparability with SoA, the subject-level scores are expressed as a proportion of the sum of all the four coefficients from the same time pressure condition. Now, just as with SoA, all scores range between 0 and 1 (except for the single negative LM-score), and the sum is always 1 when scores from the same subject and time pressure condition are added together. These cue-reliance scores can be interpreted as the share of the total distributed decision weight that is received by a cue. They will be referred to as SoD-scores (Share of Decision weight).

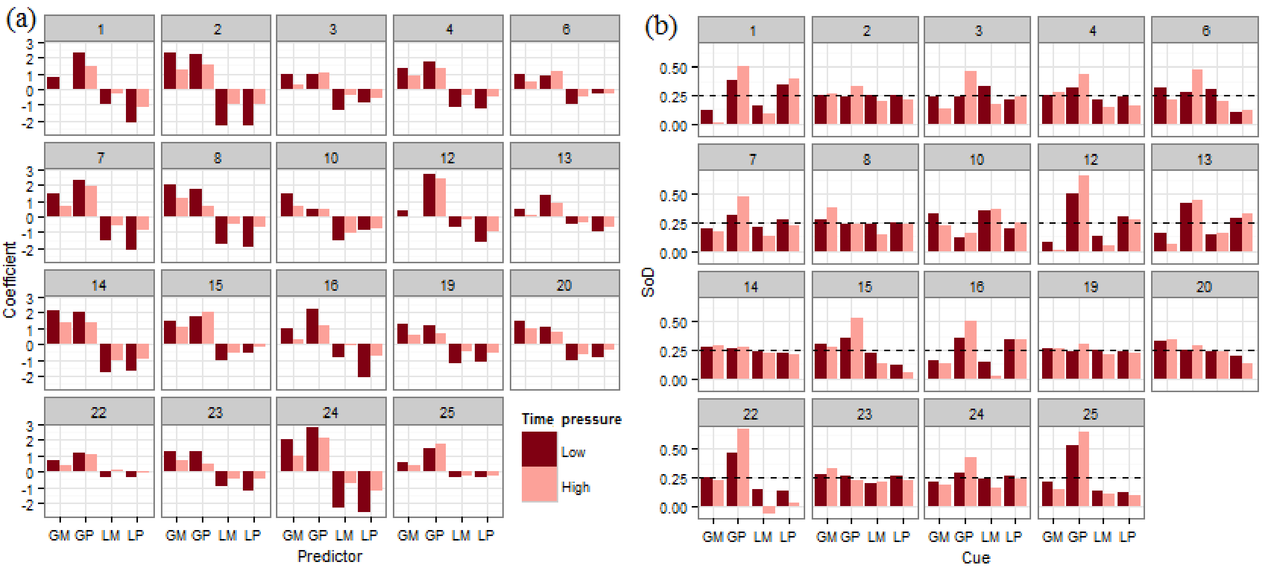


*Figure 5.* (a) The random effect coefficients for cue-predictors from the logistic regression predicting choices from cue-values. Dark red is for low time pressure, light red is for high time pressure. (b) SoD-scores for each subject, obtained by expressing absolute values of the coefficients from the same subject and condition as a proportion of their sum.

**Predicting SoD from cue type and time pressure condition.** As SoD-scores share so many of the properties of the SoA-scores, similar analyses to those performed on SoA can now be carried out on the SoDs, to investigate how decision weight is distributed between cues. An important difference between SoA and SoD is that while there were SoA-scores for each cue on every trial, SoD-scores can only be calculated for large blocks of trials. There is only one SoD-score for each cue per time pressure condition (4 cues × 2 conditions = 8 SoD-scores per subject). This means that the analysis where SoA was predicted from the combination of time pressure and information-type of a cue is performed with random effect coefficients for cue-type only, without adding random effects for how SoD interacts with time pressure. There is only one data-point per interaction per participant, so there are no dependencies between multiple observations of interactions between cue-type and time pressure. The following regression model was then fitted, to investigate group-level tendencies in the distribution of SoD:

$$\boldsymbol{SoD_{ij}} = -1 + (\gamma_1 + u_{1j})\boldsymbol{GM_{ij}} + (\gamma_2 + u_{2j})\boldsymbol{GP_{ij}} + (\gamma_3 + u_{3j})\boldsymbol{LM_{ij}} + (\gamma_4 + u_{4j})\boldsymbol{LP_{ij}} + \gamma_5\boldsymbol{GM_{ij}}\times\boldsymbol{time_{ij}} + \gamma_6\boldsymbol{GP_{ij}}\times\boldsymbol{time_{ij}} + \gamma_7\boldsymbol{LM_{ij}}\times\boldsymbol{time_{ij}} + \gamma_8\boldsymbol{LP_{ij}}\times\boldsymbol{time_{ij}} + r_{ij}$$

(See *SoD = Cue × Time* in Table 2.) The model mirrors the first SoA-model (model nr 1 in Table 2, *SoD = Cue × Time*) except that it does not assume that interactions depend on the identity of the participant (in the SoA model, this assumption is made through having random effects for cue-predictors in both high and low time pressure). SoD-scores (centered on 0.25) are predicted from which cue the score is connected to, under which time pressure condition . $\boldsymbol{GM_{ij}}$, $\boldsymbol{GP_{ij}}$, $\boldsymbol{LM_{ij}}$ and $\boldsymbol{LP_{ij}}$ are dummy-variables, indicating what cue an SoD-score is associated with: G is for gain, L is for loss, M is for magnitude and P is for probability. Random slopes are added for these predictors to account for the fact that there are two observations of each of them per participant (one for each time-condition). $\boldsymbol{time_{ij}}$ is a dummy-variable signifying the time pressure condition, coded 0 for low pressure and 1 for high pressure. Potential differences between participants in a general effect of time pressure are not accounted for by the model, since the four SoD-scores by definition sum to 1 in both time pressure conditions.

The coefficients (see Figure 6) are very similar to those from the analysis of eye tracker data (see Figure 7, with SoA- and SoD-scores plotted together, for ease of comparison). Once again, GP is shown to have an average reliance-score significantly above 0.25 in both time pressure conditions at 0.32 in low pressure ($\gamma_2$ = .068, $t$(45.8) = 2.33, $p$ < .05) and .43 in high pressure ($\gamma_6$ = .107, $t$(45.8) = 6.47, $p$ < .001). And LM once again is relied on the least, on average, with an SoD of 0.22 in low pressure ($\gamma_3$ = -.034, $t$(45.8) = -1.50, $p$ = .14) and at 0.15 in high pressure ($\gamma_7$ = -.066, $t$(45.8) = -2.98, $p$ < .001).

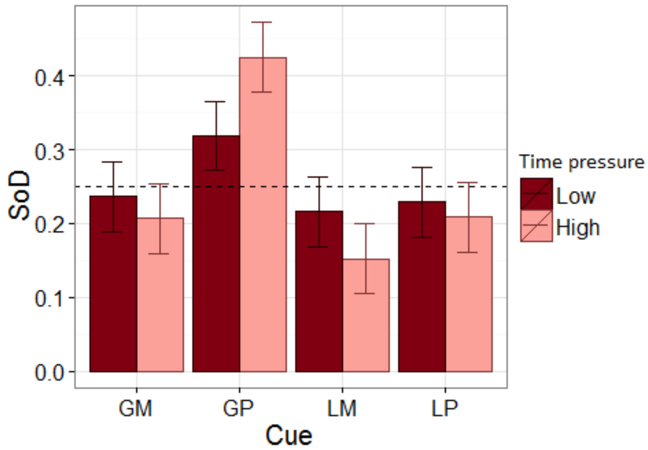

*Figure 6.* Results from regression predicting SoD from cue-type and time pressure, representing average SoDs across subjects. Low pressure bars are the fixed effect coefficients for each cue, while high pressure bars are fixed effect coefficients plus interaction coefficients. Error bars signify 95 % CI.

***The distribution of decision weight and the influence of time pressure.*** A comparison between the SoD-model above and an empty model (*SoD = empty*) showed that the full model had explanatory relevance ($\chi^2(16) = 226.4$, $p < .001$). Contrasts to investigate main effects of valence (gain vs loss) and dimension (probability vs magnitude) as were done for the SoA-model, are repeated for SoD:

$$\boldsymbol{SoD_{ij}} = -1 + (\gamma_1 + u_{1j})\boldsymbol{GvsL_{ij}} + (\gamma_2 + u_{2j})\boldsymbol{PvsM_{ij}} + r_{ij}$$

(See *SoD = GvL + PvM* in Table 2.) Both ***GvsL*** (a dummy-variable taking the values 1 for gain cue-SoDs and -1 for loss cue-SoDs) and ***PvsM*** (taking the values 1 for probability-SoDs and -1 for magnitude-SoDs) were significant predictors ($\gamma_1 = .047$, $t(18) = 4.10$, $p < .001$; $\gamma_2 = .047$, $t(18) = 2.91$, $p < .01$). It can thus be inferred that participants generally prioritized gains over losses and probabilities over magnitudes in making their choices.

To investigate if decision weight was distributed differently between time pressure conditions, the full SoD-model, with predictors for all combinations of cue-type and time-condition, was compared with a simpler model that predicted SoD from cue-type alone (*SoD = Cue* in Table 2), without differentiating between time pressure conditions. The full model was found to provide a significantly better fit to the data ($\chi^2(4) = 71.1$, $p < .001$), indicating that time pressure did influence the distribution of SoD-scores.

The appropriate contrasts to further explore the source of difference between the distribution of SoD in low and high time pressure have already been carried out, through the interaction terms in the full SoD-model. GP, the only cue significantly above 0.25 in low time pressure, had a significant interaction with time pressure, in the direction predicted by focus narrowing ($\gamma_6 = .107$, $t(45.8) = 6.47$, $p < .001$). LM, which was the cue attended least under low pressure, also interacted significantly with time pressure, in that decision weight on LM decreased further ($\gamma_7 = -.066$, $t(45.8) = -2.98$, $p < .001$).

**Correspondence between SoD and SoA.** The similarity of the results from analyses of SoA and SoD suggest that the two measures of cue-reliance correspond well. To test this, the following mixed effects regression model was fitted:

$$\boldsymbol{SoD_{ij}} = (\gamma_0 + u_{0j}) + (\gamma_1 + u_{1j})\boldsymbol{SoA_{ij}} + r_{ij}$$

(See *SoD = SoA* in Table 2.) The SoA-scores used as predictors here are the subject-level coefficients from the SoA-model, representing average SoAs for each combination of cue-type and time pressure. This means that there is one SoA-score for each SoD-score. An interaction between SoA and time pressure was not added to the model, as it did not significantly improve model fit ($\chi^2(2) = 0.86$, $p = .64$) (see *SoD = SoA × Time* in Table 2).

The relationship between SoD and SoA is thus assumed not to depend on the time pressure condition.

SoA-scores significantly predicted SoD-scores, $\gamma_1 = 0.67$, $t(14.6) = 12.3$, $p < .001$. Figure 7 illustrates the relationship (see also Appendix, for plots of subject-specific reliance-scores). SoD and SoA correlate at $r = .71$. The correlation is $r = .62$ in low pressure and $r = .74$ in high pressure (all correlations significant at $p < .001$).

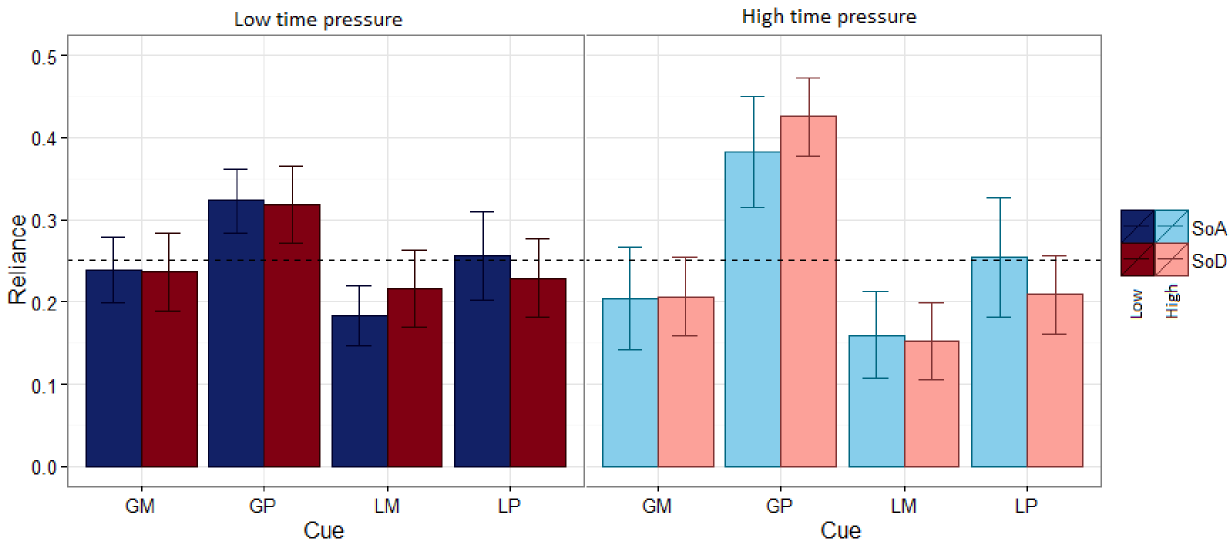


*Figure 7.* Fixed effects from regressions predicting SoA and SoD from cue-type and time pressure, plotted together. Error bars indicate 95 % CI. Dotted line is the average of 0.25. Blue is for SoA, red is for SoD. Dark colors are for low time pressure, bright colors are for high time pressure.

**Predicting the effect of time pressure from individual information-preferences**

Up to this point, the predictions tested from the focus narrowing hypothesis have all been made for the effect of time pressure on cue-reliance scores that are averages across subjects. As explained in the introduction, a problem with only investigating group averages is that they hide how the effect of time pressure could depend on subject-level factors. The focus narrowing hypothesis predicts that the effect of time pressure depends on how the subject evaluates the relative importance of the cues. To test this hypothesis more directly, the effect of time pressure on the reliance-score of a cue is predicted from that cue's reliance-score in the low pressure condition:

$$\boldsymbol{SoR\_Change_{ij}} = (\gamma_0 + u_{0j}) + (\gamma_1 + u_{1j})\boldsymbol{SoR\_t0_{ij}} + r_{ij}$$

(See *SoR_Change = SoR_t0* in Table 2.) As the two measures of cue-reliance (SoA and SoD) correspond well, they are combined into a single measure for this analysis. SoR (Share of Reliance) is the average of SoA and SoD. ***SoR_Change*** represents how SoR changes from low to high pressure. It is calculated by subtracting a subject's SoR-score for a cue in low pressure from the same subject's SoR-score for that cue in high pressure. A negative ***SoR_Change***-value thus means that reliance on a cue decreased under time pressure for that subject, while a positive value means that reliance on the cue increased. The predictor, ***SoR_t0***, is simply the SoR-score in the low pressure condition. To make the value of the intercept ($\gamma_0$) more informative, ***SoR_t0*** is centered on its average value of .25. This way, the intercept represents the predicted effect of time pressure on a cue with an average SoR-score, rather than the effect on a cue with an SoR of zero.

The prediction from focus narrowing is that the coefficient for the slope ($\gamma_1$) will be positive. This would mean that the model's predictions for the effect of time pressure would align with those of the focus narrowing hypothesis: Cues receiving high SoR-scores under low pressure would then be predicted to receive even higher scores under high pressure, and cues receiving low SoRs would be predicted to be relied on even less.

As predicted, ***SoR_t0*** was a significant predictor of the effect of time pressure on cue-reliance, and the slope was indeed positive ($\gamma_1$ = .613, $t(9.3)$ = 4.47, $p$ = .001). The intercept was very close to zero ($\gamma_0$ = -.001, $t(9.3)$ = -0.16, $p$ = .88), indicating that 0.25 is the point where the predicted effect of time pressure on cue-reliance shifts from being a decrease to being an increase (as illustrated by the green lines in Figure 8, and the green line in Figure 9). For every unit SoR in low pressure increases/decreases relative to .25, the predicted effect of time pressure increases/decreases by approximately half a unit (as the slope is .613).

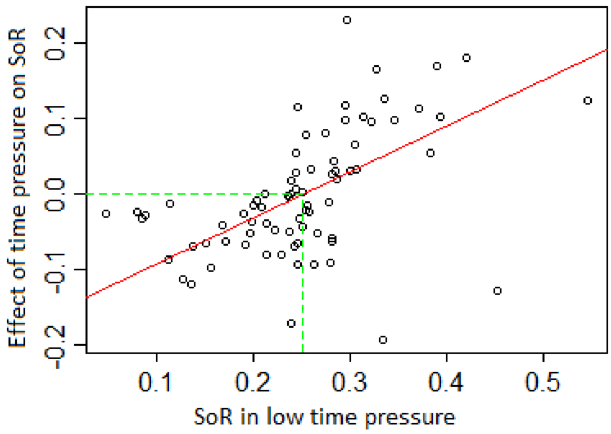


*Figure 8.* Scatterplot of the SoR_Change-model. SoR-scores in low time pressure (i.e. ***SoR_t0***), plotted against the effect of time pressure on SoR (i.e. ***SoR_Change***). The regression line is plotted in red. Dotted green lines illustrate that the model predicts no effect of time pressure when ***SoR_t0*** is 0.25.

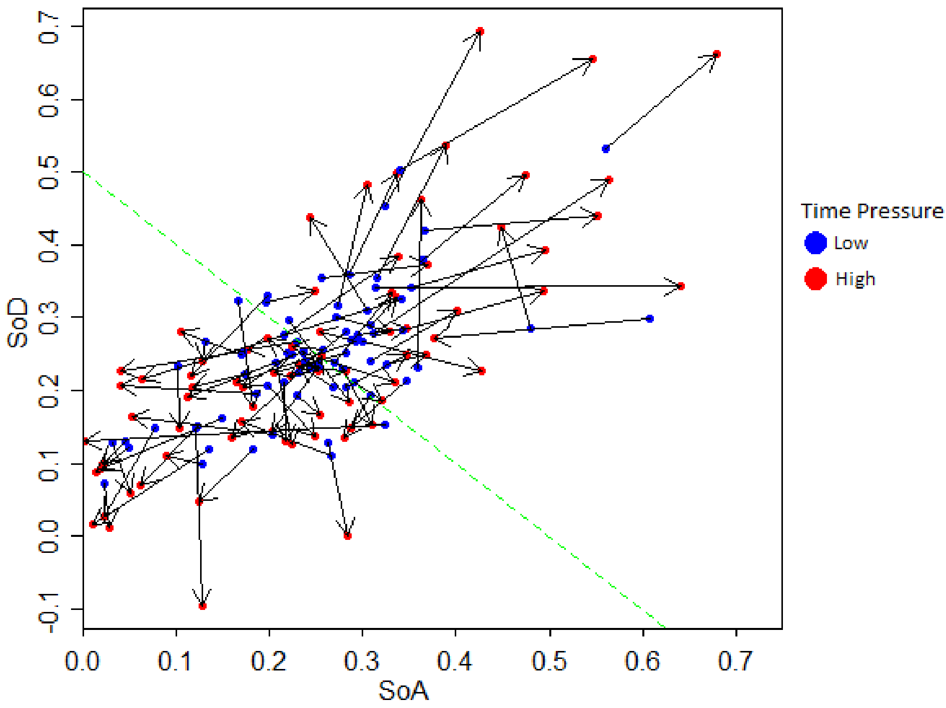


*Figure 9.* Illustration of the focus narrowing effect. Subject-specific SoA- and SoD-scores are plotted against each other. Blue dots are from the low time pressure condition, red dots are from the high time pressure condition. Dots belonging to the same cue and the same subject are connected with arrows, indicating the effect of time pressure on the reliance-scores. The green line indicates where the average of SoA and SoD (i.e. SoR) equals 0.25. Focus narrowing predicts that reliance-scores will move away from this line under time pressure. (The plot also illustrates the correspondence between SoA and SoD.)

Table 2.
*Key statistics for all regression models*

| Nr. | Regression model | n | df | logLik | AIC | Comp. Nr. | $\chi^2$ |
|---|---|---|---|---|---|---|---|
| 1 | *SoA = Cue × Time* | 23808 | 20.07 | 10721.4 | -21352.8 | | |
| 2 | *SoA = Empty* | 23808 | 17.84 | 4391.2 | -8776.4 | 1 | 12660*** |
| 3 | *SoA = GvsL + PvsM* | 23808 | 20.06 | 8938.7 | -17865.4 | | |
| 4 | *SoA = Cue* | 23808 | 20.06 | 9493.3 | -18956.7 | 1 | 2456.1*** |
| 5 | *SoA = GP_inc + LM_dec* | 23808 | 20.05 | 4625.4 | -9559.6 | | |
| 6 | *Gini = Time* | 5952 | 17.98 | 2665.7 | -5319.3 | | |
| 7 | *P(accept) = CueVal × Time* | 6059 | | -2572.3 | 5274.7 | | |
| 8 | *SoD = Cue × Time* | 152 | 45.80 | 214.3 | -390.7 | | |
| 9 | *SoD = Empty* | 152 | 18 | 101.1 | -196.3 | 8 | 226.4*** |
| 10 | *SoD = GvsL + PvsM* | 152 | 18 | 150.2 | -288.5 | | |
| 11 | *SoD = Cue* | 152 | 18 | 178.8 | -327.6 | 8 | 71.1*** |
| 12 | *SoD = SoA* | 152 | 14.60 | 150.4 | -288.7 | | |
| 13 | *SoD = SoA × Time* | 152 | 26.89 | 150.8 | -285.6 | 12 | 0.8 |
| 14 | *SoR_Change = SoR_t0* | 76 | 9.31 | 94.1 | -176.3 | | |

"Nr." indexes the models; "Regression model" is the name of the model, indicating the prediction made; "n" is the number of observations; "df" is the degrees of freedom (df for mixed models approximated using the Kenward-Roger approximation (Kenward & Roger, 1997), except for the logistic regression, where it does not apply); "likelihood" is the log-likelihood statistic; "AIC" is Akaike's Information Criterion; "Comp. Nr." indicates which model, if any, the current model is compared to; "$\chi^2$" is the chi-squared statistic for likelihood ratio tests. *p<0.05, **p<0.01, ***p<0.001.

# Discussion

The aim of this study was to investigate information utilization in risky decisions made under high- and low time pressure. A gambling-task, where four information-cues were equally predictive of the expected value of a gamble, was performed while time pressure was manipulated within subjects. Information utilization was measured using mixed effects regression analyses of both eye tracking data and behavioral data.

Two competing hypotheses about how time pressure influences information use were proposed. The loss-hypothesis, based on conclusions drawn in prior studies, predicted that time pressure would have the effect of increasing reliance on information about losses. The focus narrowing-hypothesis, which is novel to this study, predicted that time pressure would increase reliance on the information considered the most central to performing the task, and decrease reliance on the information deemed least central. The effect of time pressure would then depend on how the decision maker evaluated the relative importance of the four pieces of information in the task.

On the group level, the results from both eye tracking and behavioral data showed that participants generally preferred to rely on gain- over loss information, and probability- over magnitude information. In line with the focus narrowing hypothesis, and contrary to the loss hypothesis, these tendencies to favor gain- and probability information were intensified under time pressure.

The focus narrowing hypothesis also predicted the finding that participants distributed their attention less evenly between information-cues under time pressure, as indicated by higher average Gini-coefficients. The main prediction from focus narrowing was that time pressure would have the effect of pushing subject's information reliance-scores away from the average: low SoA- and SoD-scores should get even lower, high scores even higher. This prediction was also supported, but the findings can also be interpreted as time pressure simply causing increased reliance on gain-probabilities.

## Information utilization

**Correspondence between attention and decision weight.** Information utilization was analyzed both by measuring the share of visual attention each cue received (SoA) and by estimating how well the values of a cue predicted the responses made (SoD). The two measures, SoA and SoD, were shown to correlate quite strongly, both under high and low time pressure ($r = \sim.65$ in both conditions). This provides support for the notion that visual attention is distributed between cues according to how much decision weight is assigned to each cue. Additionally, there could be causation in the opposite direction as well; attention could cause the decision weight of information to increase. As described in the introduction, there is a rapidly growing amount of studies to support such an effect (e.g., Krajbich & Rangel, 2011). Still, the data of the current experiment do not allow strong conclusions one way or the other about the causal relationship between attention and decision weight.

**Reliance on gains and probabilities.** The task was designed so that the four cues - gain magnitude (GM), gain probability (GP), loss magnitude (LM) and loss probability (LP) - were equally useful for solving the task in accordance with classical principles of rationality. A risk neutral decision maker only caring about maximizing the expected value of each choice would rely equally on all four cues. Yet, the distributions of reliance-scores between cues differed substantially from even distributions. This was true whether cue-reliance was measured using behavioral data or eye-tracking, and it was true both with and without time pressure. The pattern of what cues were relied on can be described as resulting from two effects: gain-cues were preferred over loss-cues, and probability-cues were preferred over magnitude-cues. This lead to the GP-cue being preferred the most, and the LM-cue being preferred the least. GM and LP were in the middle, being relied on about equally.

A difficulty in assessing cue importance from logistic regressions of choice data is that one can assume that cue-values contribute directly but also indirectly, as parts of interactions, to choices. Specifically, decision makers can be influenced by gain magnitude and probability, but also by their interaction, i.e. the expected gain (and correspondingly for losses). Unfortunately, the estimation of cue importance is non-trivial when a model includes interaction terms, especially in mixed effects regressions. To ascertain that the simple model without interactions does not lead to substantially different cue importance values than an analysis that includes expected gains and losses, an analyses that included cue’s main effects and their interaction was performed on all participant’s pooled data and cue importance was calculated using average predictive comparison (APC) values (c.f. Gelman & Pardoe, 2007). As in the main analysis, this analysis showed highest cue importance values for gain probability and thus supported the validity of the results.

The preference for gains over losses is surprising in light of the strong empirical basis for the claim that people typically fear losses more than they value equally large gains (Kahneman & Tversky, 1992). If you fear losses, you would presumably be better off focusing on the loss-cues, to make sure that you don’t accept gambles that have a high chance of yielding a large loss. A possible explanation for why gain-cues are still preferred is the incentive scheme that determined how much a participant was paid. In addition to a fixed sum of 150 kr, participants were paid the sum of the pay-outs from ten randomly selected trials. Crucially, however, the pay-outs from the ten trials would only be received if they added up to a positive amount. If the sum was negative, this would not be subtracted from the 150 kr that participants were guaranteed. Accepting trials that yield a loss was still punished, as it could lead to the total payment adding up to a smaller amount, but it was not punished as hard as it would have been if it had been possible to actually lose money. As there was no ceiling on gains to weigh up for the floor that was put on losses, a small imbalance was created between the gain- and loss cues.

To illustrate this, I ran simulations to estimate the expected total payment in addition to 150 kr for a participant who relies on only a single cue to do the task. He accepts when the cue is at its best value (GM = 120, LM = -30, etc.), and rejects when it is at the worst value. When the cue is at the middle value, he randomly either rejects or accepts. 100 000 simulations were run for each cue, where ten trials were randomly selected each time (the randomization of responses for trials with mid-valued cues was also repeated). When the incentive scheme had no floor on losses, the expected earnings stayed about the same regardless of what cue the participant relied on, at between 66.6 kr and 67.5 kr (standard errors all above 0.42). But, notably, the variability in the payment received differed between cues. GM had the largest variability in earnings, with a standard deviation of 156.7 kr. Then came GP (SD = 142.2 kr), then LP (SD = 127.4 kr) and lastly LM (SD = 110.5 kr). When the floor on losses was put in, these differences in outcome-variability lead to differences in the expected earnings as well. Since all variability below zero is now gone, the cue with the highest variability is now also the most profitable, on average. So, the expected earnings from relying exclusively on GM become 99.7 kr (SE = 0.36). For GP, they are 94.3 kr (SE = 0.34), for LP 89.1 kr (SE = 0.31), and for LM 84.7 kr (SE = 0.29). The ranking for how risky the cues are can be argued to have stayed the same, however. GM had the highest rate of earnings of zero kr (39143/100000), and LM had the lowest (34271/100000).

The reason why probability cues are relied on more than magnitude cues is less clear. It could be argued that the GM-cue, which is slightly more risky than GP, was found to be a bit too risky and that it wasn’t worth the slightly increased expected earning that comes from prioritizing it. But that might be expecting too much of how well participants are able to sense the long term implications of relying on the different cues.

**Time pressure**

There was a pronounced impact of time pressure on how cue-reliance was distributed. In both the choice data and in the eye tracking data, time pressure caused effects that are consistent with focus narrowing. There was an increased amount of focus on the GP-cue, which was the cue that was utilized the most also in the absence of time pressure. The LM-cue, which was predicted by prior research to receive increased focus under time pressure, was relied on significantly less when time pressure was introduced. This is also consistent with focus narrowing, as LM was the cue that was used the least in the low pressure-condition. Focus narrowing predicts that when attention shifts towards the information considered the most important, this will mainly happen at the expense of the information considered least important.

**Loss aversion and risk aversion.** Authors of prior studies on the effects of time pressure in risky decision making differ in whether they attribute their findings of increased avoidance of large losses to an increase in loss aversion (e.g., Bollard, Lui, Nursimulu, Rangel, & Bossaerts, 2007) or an increase in risk aversion (e.g., Ben Zur & Breznitz, 1981). Loss aversion means that the negative impact of a loss is felt more strongly than the positive impact of an equivalent gain, and that losses therefore will be avoided. Risk aversion, as the term is interpreted in prior studies, rather means that the decision maker seeks to keep the variability in the possible outcomes of her choices as low as possible. When gambles are similar in expected value, the gamble with the larger loss will typically also be the gamble with the most variable outcome, and it will thus be avoided.

It could be argued that the prediction of increased loss aversion under time pressure has not really been tested in this study. Losing money is only possible in a relative sense (i.e. added earnings are reduced) when the incentive scheme sets sums of the 10 selected gambles below zero to zero. An example of a payment schedule that would have allowed for losses (while still avoiding situations where participants owe the experimenter money for having taken part), could be to give participants a fixed sum at the start of testing, and to allow for the possibility that negative earnings could detract from this sum

On the other hand, it can be argued that the prediction of increased risk aversion, defined as aversion for outcome variability, *has* been tested. The more risk averse a decision maker is, the more she should prioritize the loss cues in the present task, because the variability of the expected pay-out is larger if you prioritize gain-cues over loss-cues (the risk of earning zero is higher for gain-cues). The incentive scheme can explain why gain cues are relied on more than loss cues, even if participants are risk averse, since the expected pay-out is higher for gains. But the incentive scheme cannot explain why the reliance on loss cues is further reduced under time pressure. If risk aversion increased under time pressure, reliance on loss cues would be expected to go up rather than down, as it did.

**Attention less evenly distributed under time pressure.** Decision strategies were also analyzed by calculating a Gini-coefficient for the distribution of visual attention between cues in each trial. The Gini-coefficient is a measure of inequality, which takes values between 0 and 1 (signifying perfect equality and -inequality, respectively). When the focus of attention narrows on only the most important information, attention will be distributed less evenly between cues and the Gini will be higher. Consistent with the focus narrowing hypothesis, time pressure was found to be a significant predictor of Gini.

When there was no time pressure, the average Gini was 0.28. This represents a quite even distribution of attention between cues, which makes sense in light of the high degree of accuracy most participants achieved (average of 86 % of responses in accordance with EV). The average distribution of SoA on a single low pressure trial, from the most to least attended cue, was [0.44, 0.28, 0.17, 0.10].

Under time pressure, the average Gini rose to 0.40. The average distribution of SoA-scores was then [0.55, 0.30, 0.12, 0.05]. This indicates that participants became more selective in their attention, and increased their use of heuristic strategies. The 2 second time limit should be sufficient to allow attending to all cues, as is suggested by some participants having very low mean Gini-coefficients even under high time pressure (the lowest being 0.21). A fixation can be as short as 200ms and still allow the viewer to perceive what was fixated (Holmqvist et al., 2011). And saccades shifting fixations from one cue to the next can be completed in less than 50ms. Yet, most participants chose to attend selectively to only parts of the information. This could reflect a choice to rely on simplified decision rules (i.e. heuristics) rather than attempting value-computations involving all the available information, to maintain accuracy as high as possible. Additionally, as suggested by focus narrowing, the high Gini-coefficient could reflect a narrowing of visual attention due to stress. Whether the main driver of the increased inequality in the distribution of attention is cognitive (i.e. a choice to use heuristics) or perceptual (i.e. a narrowing of focus), is not discernable from the data.

**Time pressure as an amplifier of information preferences.** While results from both the group-level information-utilization analyses and the Gini-analysis are consistent with focus narrowing, neither tests the focus narrowing hypothesis directly. It was shown that the group-level tendencies to focus most on gains and probabilities were increased under time pressure. But it is not apparent that the people who increased their focus on gains and probabilities under time pressure were the same people who focused on them the most in the absence of time pressure. Focus narrowing also predicts that those with preferences differing from the group average - those who care more about losses than gains and/or care more about magnitudes than probabilities - will have their preferences shifted in the opposite directions from the other participants. The group level analyses are silent about such effects.

Similarly, while the Gini-analysis suggests that focus was narrowed in on some of the information, it is silent about what information this was.

To investigate focus narrowing more directly, the change in subject-specific cue-reliance scores from low to high pressure was predicted from how much the subject relied on the cue in low pressure. Cue-reliance in low pressure significantly predicted the effect of time pressure on cue-reliance. Higher than average subject-level reliance-scores in low pressure thus predicted an increase in reliance on that cue from low- to high pressure, and lower than average scores predicted a decrease.

The predictions from the fitted regression-model approximate the focus narrowing effect. Most importantly, it is predicted that the most central cues will receive a further increase in focus under time pressure. But it is also specified that the cues that will be focused on less are the cues that are the least important in low pressure, rather than cues that receive a moderate reliance-score.

A weakness of the regression model is that when reliance-scores in low pressure get too extreme, the model produces predictions that are unrealistic, and sometimes even logically impossible. If a cue was to receive a very large share of attention and decision weight in the low pressure condition, say more than 60 %, then the model predicts reliance-scores in the high pressure condition that can get close to the natural ceiling of how large a share of the attention/decision weight a cue can have (100 %). Likewise, cues that are largely ignored even in the absence of time pressure can sometimes be predicted to receive sub-zero percentages of attention/decision weight under time pressure.

More sophisticated models of the focus narrowing effect, which do not make unrealistic predictions in extreme cases, are possible to construct. But for the purposes of the present study, the simple model is still sufficient.

The model clearly describes the data better than would a model of the competing hypothesis; that time pressure leads to a general increase in focus on the loss cues. The decision weight on loss cues was reduced rather than increased under time pressure in this experiment.

If, however, the competing hypothesis was that time pressure causes a general increase in focus on the GP-cue, a comparison would probably end less favorably. 10 out of the 19 participants have the GP-cue as the most important cue in the low pressure condition. And an additional 6 participants had SoR-scores above 0.25 for GP in low pressure. So in the case of these 16 participants, the two models make very similar predictions: that focus on GP goes up. The focus narrowing model only differs in that it specifies that the extent of the increase depends on the size of the share of attention, and that decision weight will mainly be shifted away from the least attended cue(s).

It could be argued that the focus narrowing hypothesis still wins out on theoretical grounds, when compared to a GP-hypothesis. As is described in the introduction, there is support for the focus narrowing account from diverse fields of research (Easterbrook, 1959; Wells & Matthews, 1994; Mather & Sutherland, 2011). The utilization of information along the GP-dimension is largely unexplored theoretically, as it is perfectly correlated with the LP-dimension in the majority of risky decision studies. Mixed-outcome gambles in most studies do not allow the possibility of receiving both a loss and a gain at the same time, as is possible in this experiment. You either receive a gain or a loss, not both. So GP is then exactly 1-LP on all trials. Therefore, few theories of risky choice discuss GP as something separate from LP. And even fewer theories, perhaps none, make suggestions as to how time pressure would influence the extent to which GP is relied on to make choices. Still, more data is needed before strong conclusions one way or the other can be drawn on this point.

## Limitations and future directions

**Low inter-subject variability in information preferences.** As outlined above, results would have been more strongly in favor of a focus narrowing effect if subjects' information preferences had been more variable in the low pressure condition (rather than most subjects relying on GP). To achieve more variability, future studies could manipulate information preferences, for instance through mood-priming or through manipulations of the payment schedule. Subjects could be primed towards different information preferences, with the prediction from focus narrowing being that these manipulated preferences would then be further amplified under time pressure.

An alternative approach to increasing variability in information preferences is to have a screening phase of the experiment, and to selectively recruit subjects to the main-phase so that variability in cue-reliance is maximized.

**Task relevance or salience as the determinant of focus.** If a focus narrowing effect is accepted as an explanation of findings in this experiment, a question still remains as to exactly what determined which cues were focused on and which cues were neglected under time pressure. Most of the theories and studies that formed the basis of the focus narrowing hypothesis point to task relevance - stressors such as time pressure lead to increased focus on the information that is most relevant to reaching current goals (e.g., Easterbrook, 1959). Top down attentional systems become better able to divert our attention away from irrelevant distractors. But in a recent theoretical review, Mather and Sutherland (2011) suggested that stress rather has the effect of increasing focus on the most attentionally salient aspects of the environment, regardless of whether salience is due to top down- or bottom up factors.

In the present study, task relevance and salience can be argued to be almost perfectly confounded. Task relevance is a strong determinant of how attention grabbing something is. Most bottom-up factors influencing how attentionally salient the cues were - differences in color, luminance, position, size, shape, emotional impact, etc. - were either controlled for or counterbalanced. So the cues that received increased focus under time pressure were at the same time both the most task relevant and the most salient.

It is, however, easy to imagine risky decisions without a complete correspondence between the relevance- and the salience of information. Like for instance the decision of buying a lottery ticket. Advertisements for lotteries tend not to highlight the gain probability, even though it is undoubtedly a relevant piece of information. Rather it is the gain magnitude, the grand prize, that advertisers try to make as salient as possible. The question is then: will time pressure make you focus more on how big the grand prize is, or on how improbable it is that you'll win it? Will time pressure make you focus more on what is salient or on what is relevant? The impact of manipulations of salience in risky decisions under varying levels of time pressure could be an interesting topic for future research.

**The role of arousal.** Future research could also investigate how a focus narrowing effect of time pressure depends on the level of arousal that is experienced. Theorists disagree on the role of arousal in mediating increased attentional selectivity in the face of stressors such as time pressure. Some argue that it is the arousal induced by the stressor, rather than the stressor in and of itself, that leads to a narrowed focus of attention (Edland, 1994). Others argue that a narrowing of attentional focus is an adaptive strategy when a stressor restricts your decision making resources, and that the effect does not depend on arousal (Payne, Bettman & Johnson, 1988). Pupillometry could be informative in investigating this question, as increased pupil dilation has been shown to be an indicator of arousal (Laeng, Sirois & Gredebäck, 2012). But as pupil dilation is also influenced by other factors, such as cognitive load and the intensity of cognitive activity, it might be best applied in combination with other stress measures, such as skin-conductance response and/or self-report forms.

**Focus narrowing without heuristics?** It is not clear from this study that the focus narrowing effect also occurs in situations where decision makers do not increase their reliance on heuristics under time pressure. As cue-reliance was measured in relative terms (how large a *share* of the total attention/decision weight each cue received) rather than in absolute terms, the increased tendency to ignore cues implied that the cues that remained in attention received higher cue-reliance scores. When there are fewer cues between which fixation time and decision weight are to be shared, the cues will tend to get larger shares.

It is perfectly possible for time pressure to exist even if you have the time and capacity to consider all the information relevant to your risky decision problem (Maule & Hockey, 1993). If no information is ignored, a focus narrowing effect would not only require that time pressure causes attention to be distributed less evenly between each piece of information. It would also require that when a piece of information gets an increased share of attention, that information's impact on choices also increases. As mentioned previously, there are studies that suggest such an effect of attention on decision weight (e.g., Krajbich & Rangel, 2011). But more research is needed before the finding of a focus narrowing effect of time pressure can be generalized to risky decisions where heuristics are not used.

## Conclusions

This study aimed to investigate the effect of time pressure on risky decision making, comparing predictions from prior studies with predictions from the novel focus narrowing hypothesis. Time pressure was manipulated within subjects, while multiple trials of a gambling-task were performed. In the task, information about the magnitudes and probabilities of a gain and a loss was used to determine whether or not a gamble should be accepted. Information preferences were measured separately for each subject, using mixed effects regression analyses on both eye tracking- and behavioral data.

Prior studies of risky decision making under time pressure have concluded that time pressure has a general effect of decreasing decision makers' willingness to take risks. The results of the present study were inconsistent with such a conclusion. The increased overall tendency to rely on gain probabilities under time pressure suggested that the willingness to take risks went up rather than down.

In contrast, the results were consistent with a focus narrowing effect of time pressure in risky decisions. Time pressured decision makers were found to further increase their focus on the information already relied on most strongly in the absence of time pressure, and to decrease their focus on the information relied on least. The effect of time pressure is thus suggested to interact with the characteristics of the decision maker, such that it amplifies pre-existing information preferences.

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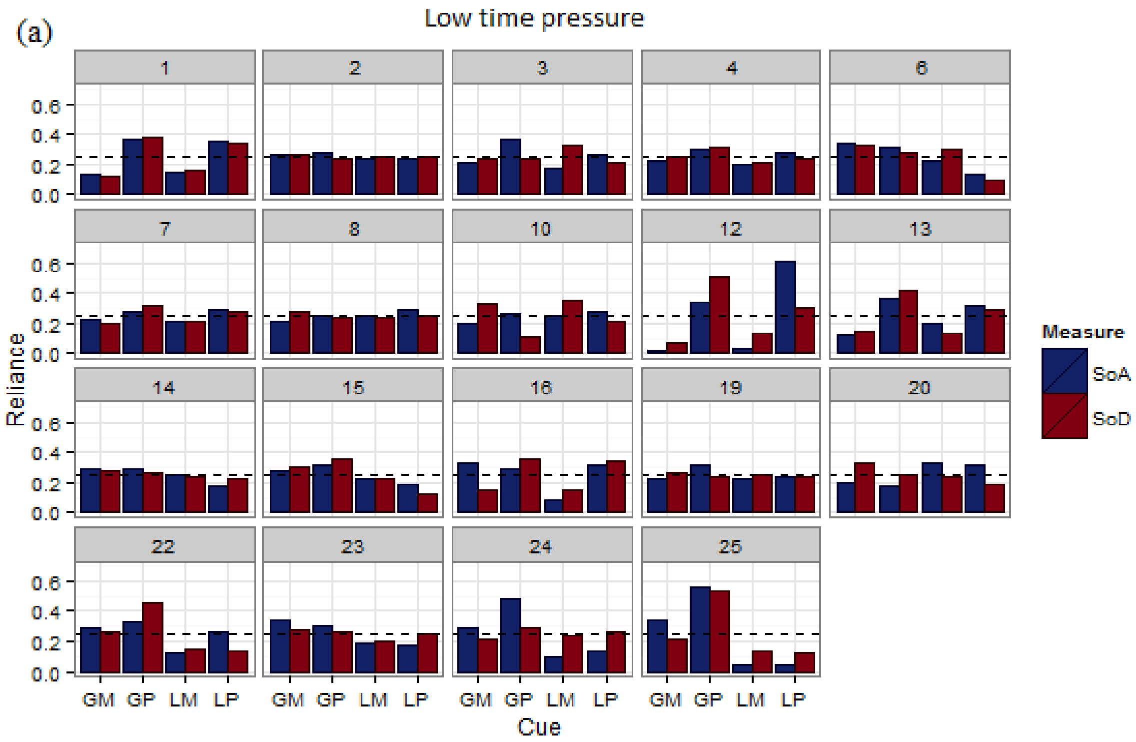
# Appendix

Information reliance scores for each subject from eye tracking- (SoA) and behavioral data (SoD), plotted together. Plot (a) has scores for each cue from the low time pressure condition, plot (b) has scores for each cue from the high time pressure condition. Blue is for SoA, red is for SoD. Dark colors are low time pressure, bright colors are high time pressure.

(a)




(b)