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Testing Biased Competition Between Attention Shifts: The New Multiple Cue Paradigm

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While the classic Posner cuing paradigm has been used to study cuing of a single endogenous shift of attention, we present a new multiple cue paradigm to study the competition between multiple endogenous shifts of attention. The new paradigm enables us to manipulate the number of competing attention shifts and their relative importance. In three experiments, we demonstrate that the process of selecting one among other relevant attention shifts is governed by limited capacity and biased competition. We show that the probability of performing the most optimal attention shift is influenced by the total number of attention shifts competing for execution and that reward is a determining factor for the selection between attention shifts. We explain our results with a recent mathematical model of biased selection of response sets (the model of intention selection [MIS]). Our new paradigm offers a critical test of MIS and is an important new tool for investigating the mechanisms underlying the retrieval of response sets from long-term memory (LTM). The model (MIS) and the new multiple cue paradigm can provide a new perspective on LTM representations of response sets for instrumental action and on habitual and goal-directed processing in action control.

Public Significance Statement

We show that the competition between shifts of attention is dependent on the number of cues and the relative reward associated with each shift of attention. Our digital life is dominated by multiple cues for attention weighted by the prospect of social reward. Our experiments and mathematical model provide insights into the selection mechanisms involved in the simultaneous cuing of multiple attention shifts. Mechanisms that are being manipulated by social media algorithms.

Keywords: multiple cues, biased competition, habitual processing, goal-directed processing, selective attention

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Human agents operate in a noisy world with many simultaneous tasks engaging one’s attention. Given multiple tasks, attention will simultaneously be cued in many different directions. Only rarely will agents find themselves in a situation where a single signal directs the agent to attend to a particular object or location. Expressed in terms of the classic Posner cuing paradigm (Posner, 1980; Posner & Cohen, 1984), only rarely will agents find themselves in situations with only a single endogenous cue instructing the agent to attend to a single location. Ordinarily, agents operate in situations with multiple cues simultaneously directing the agent to different objects or locations. In this article, we demonstrate that in multiple cue conditions, agents are able to flexibly select an endogenous attention shift based on its relative reward. We show not only that agents are able to simultaneously prepare multiple shifts of attention to multiple targets but also that the final selection and execution of an attention shift are flexibly controlled by associated reward values. Despite extensive training of the cue–attention shift association, shifts of attention remain sensitive to rewards in the context. In a world with many digital cues and social media algorithms vying for our attention by constantly adjusting their rewards, insights into the reward-based biased competition process are important.

Endogenous Shift of Attention, S–R Processing, and R–O Processing

The classical Posner task for selective attention distinguishes between endogenous and exogenous shifts of attention. An example of an endogenous cue could be an arrow pointing to a left or a right location and an exogenous cue could be a flash of light around the left or the right location. The endogenous shifts of attention are usually considered to be voluntary and satisfy standard criteria for goal-directed action. According to a dominant view in both animal and human psychology, an instrumental action is goal-directed if it satisfies two criteria (Balleine & Dickinson, 1998; Balleine & O’Doherty, 2010; Dickinson & Balleine, 1994; Dolan & Dayan, 2013). First, the action is explained by the agent’s belief about the response–outcome (R–O) contingency. Second, the action is explained by its sensitivity to reward. This means that if the agent’s action changes in response to changes in the R–O contingency or in response to changes in reward (e.g., devaluation), then the action is goal-directed. In the classic Posner task, the agent’s covert endogenous shift of attention is sensitive to changes in both R–O contingencies and reward. In the classic setup, the cue is valid 80% of the time (Posner, 1980; Posner & Cohen, 1984). That is, 80% of the time there will be a relationship between shifting attention to the location indicated by the cue and detecting a stimulus. If the agent learns about changes to this probability of the R–O contingency, they alter how they shift their attention (Eriksen & Yeh, 1985; Jonides, 1980; Madden, 1992; Riggio & Kirsner, 1997). That is, the agent can flexibly shift attention to another location or refrain from shifting attention if they learn about altered R–O contingencies. Furthermore, the agent can also alter how they shift their attention if the reward values of the R–O contingencies change, for example, if the experimenter increases the value of a cue that was previously not associated with reward and correspondingly decreases the value of a cue that was previously associated with reward (Lynn & Shin, 2015; Pool et al., 2014).

Animal and human psychology of action control often assumes that repeated performance of a goal-directed action in response to the same cue produces a habit-like learning of an association between stimulus and response (S–R association; Balleine & Dickinson, 1998; Balleine & O’Doherty, 2010). Consequently, a repeated goal-directed action is under the control of two types of processes (Dolan & Dayan, 2013). On the one hand, perception of a stimulus activates the associated response (S–R processing). On the other hand, beliefs about R–O contingencies and rewards flexibly influence the response (R–O processing). The two types of processing are involved in the control of the endogenous shifts of attention in the Posner task. The Posner task involves repeated training of how cues (e.g., a right pointing arrow) are related to shifts of attention. After training, perception of the stimulus (the right pointing arrow) activates the response (shifting attention to a location on the right). However, shifting attention is not a purely habitual process. The response (the attention shift) is also under the control of beliefs about contingencies and rewards. That is, in the classic Posner task, S–R processing is involved in learning “right pointing arrow—shift attention to right location” and R–O processing is involved in “shift attention to the location to detect the stimulus and collect the reward.” Consequently, endogenous shifts of attention are often a form of instrumental action (Buehler, 2023; Watzl, 2017; Wu, 2023), that is, they are controlled by the agent’s beliefs about the response–outcome (R–O) contingency and the associated rewards.

Preparing Multiple Attention Shifts, Two-Step Account, and Biased Competition Account

The classic Posner task is a situation with only one cue. Typically, the cue is valid 80% of the trials. Consequently, on 20% of the trials, despite the cue arrow pointing to the right, the target appears to the left of fixation. This means that on any given trial there are two possible target locations and two possible shifts of attention. In the present study, we ask how the participant prepares these attention shifts and selects between them. In contrast to the classic Posner cuing paradigm, we are interested in creating situations that enable us to directly study the selection between multiple relevant shifts of attention. Where the classic Posner task manipulates the R–O contingencies (the probability of valid trials) but keeps the number of cues and their associated rewards constant, here we keep the probability of valid cue–target associations fixed but manipulate the number of cues and their associated reward values.

In visual attention research, biased competition is often thought to take place between representations of external objects as they compete for encoding into short-term memory (Bundesen et al., 2005; Desimone & Duncan, 1995). Here, we propose a related biased competition account for the selection of shifts of attention (or, more generally, response sets), according to which multiple cues simultaneously activate multiple shifts of attention that all compete for execution weighted by their respective reward values. Our hypothesis is similar to results in a number of other domains of decision making and action control. In the domain of motor control, Cisek and Kalaska (2005) showed that when a monkey is visually presented with two different motor targets, directionally tuned cells in the monkey’s premotor cortex seem to be preparing both reaching actions in parallel. Related results have been demonstrated in humans. The parallel preparation of responses or choices has been demonstrated in various decision tasks, such as in simple reaching tasks (Freeman et al., 2011; Selen et al., 2012; Song & Nakayama, 2009) and lexical decision tasks (Barca & Pezzulo, 2012; Lepora &
Pezzulo, 2015). Competition between multiple plans or responses is also central to a number of models for go/no-go tasks (Verbruggen & Logan, 2009), task switching (Logan & Gordon, 2001; Vandierendonck et al., 2010), and prospective memory (Gründbaum et al., 2021; Strickland et al., 2018). Here, we present a new paradigm to test the claim that multiple endogenous shifts of attention are prepared in parallel and compete for execution weighted by their reward value.

Some biased competition theories of visual attention understand spatial attention as the effect of action selection (e.g., moving one’s eyes or grasping an object) rather than as a covert mental action selected on its own (W. X. Schneider, 1995). Both perspectives can be correct. It depends on where in the hierarchy of actions and plans we put our emphasis. As we argued above, shifting one’s spatial attention can be a voluntary instrumental action. Something we do in order to do something else that will result in a reward. The same can be said of grasping actions: The agent grasps something in order to eat it to obtain the reward. Just as the brain can simultaneously prepare many different grasping movements, we claim that it can prepare many different shifts of attention.

We are not in this article committing ourselves to any particular theory of spatial attention. But one could conceive of endogenous spatial attention as a matter of voluntarily turning up the sensitivity to specific objects or locations. Along the lines of Logan and Gordon’s (2001) ECTVA model, we can think of a shift of attention as a unified set of parameter values. Instead of being specified and encoded from scratch on every trial with a new task, due to over-training, the set of parameter values (in our terminology a response set) can simply be retrieved from long-term memory (LTM) (as proposed by Logan & Bundesen, 2003). If shifts of attention (understood as sets of parameters or response sets) are associated with cues through extensive training, then presentation of several cues could activate several shifts of attention (i.e., sets of parameters or response sets). If cues are associated with rewards, the selection competition between shifts of attention or response sets could be biased by their reward values.

To be sure, biased competition is not the only way to understand the selection of a spatial shift of attention. There are at least two basic ways to account for processing and decision making in a situation with multiple cues for shifting attention, where different shifts of attention are associated with different rewards. First, we might account for the selection of an attention shift among many possible shifts as a sequence of two discrete steps. In the first step, the agent identifies the cue associated with the highest reward. This step concludes with the visual selection of a single cue. In the second step, the agent shifts attention in accordance with the cue. This second step is like a classic single-cue Posner task. Let us call this account the two-step account. Second, we might account for the selection of an attention shift among many possible shifts as the outcome of a biased competition race among several shifts prepared in parallel. The competition is biased by the reward value associated with an attention shift, and the winner is executed. Call this the biased competition account. According to the biased competition account for selection of shifts of attention, we can think of a trained endogenous shift of attention as a learned combined set of S–R and R–O response sets (Verbruggen & Logan, 2009). With multiple cues, multiple response sets are activated and compete for execution. That is, with training, the attention shifts get represented in LTM as S–R and R–O response sets.

The response sets are assigned a weight relative to the associated reward in the context. In a multiple cue situation, multiple S–R and R–O response sets compete for execution where the winner is implemented as a shift of attention to an associated location. By contrast, according to the two-step account, once the first stage of visual processing has been completed and the cue associated with highest reward has been identified, there is only one relevant shift of attention to select.

Biased Competition Between Multiple Attention Shifts: The Model of Intention Selection (MIS)

Recently, Gründbaum et al. (2021) proposed a mathematical model (the MIS) of the type of selection processes that might underly the selection of a shift of attention among a plurality of relevant shifts. The core assumption of their model is that, at a given point in time, response sets (in our case covert endogenous shifts of attention) are selected for execution from LTM with a certain probability. Each response set’s probability of being selected is determined by a parameter reflecting the match between the current context and this particular response set’s representation in LTM, a parameter reflecting the perceived importance of the response set (increasing with the associated reward value), and a bias parameter (which functions like a vote for or against activating a particular aspect of this particular response set). All three parameters are multiplicatively combined in such a way that response sets (in our case, shifts of attention) that do not match the context at all or are unimportant (no associated reward) are not selected for execution at a particular point in time.

Formally, MIS represents the three factors (matching, importance, and bias) by a single unified rate equation specifying the rate of processing, \( \lambda(\chi, k) \), of component \( k \) of response set \( \chi \):

\[
\lambda(\chi, k) = \psi(\chi, k)B_k \sum_{i \in I} \omega_i, \tag{1}
\]

where \( \psi(\chi, k) \), the matching parameter, is the contextual support in the environment for response set \( \chi \) having component \( k \in K \), and \( K \) is the set of the three components of the response set. According to Gründbaum et al. (2021), each response set is constituted by a stimulus component, a response component, and a propositional goal component (we have altered some of the names for the components of MIS slightly in order to fit the context of shifts of attention). Together these components represent the S–R and R–O associations. The importance factor related to reward, \( \omega_i/ \sum \omega_i \), represents the relative weight of a response set \( \chi \) compared to the set \( I \) of all response sets. Thus, the individual weights for each response set, \( \omega_i \), enter the equation relative to the sum of the weights of all response sets in LTM, \( \sum \omega_i \). This effectively limits the sum of all \( \lambda(\chi, k) \) values, which corresponds to the total processing capacity for the selection of shifts of attention. Finally, the bias factor is represented by parameters, \( B_k \), the bias toward activating component \( k \) independently of the matching and the importance of response set \( \chi \).

MIS implements limited capacity by the relative importance fraction (cf. Equation 1). If the match between relevant response sets and the perceptual context is the same for all the response sets (i.e., their S–R representations are all equally matched by stimuli in the context), the importance weight ascribed to each response set will determine the probability of selection for execution. Assume for simplicity that the selection race between response sets or shifts of attention has a fixed limited working memory capacity where one
and only one shift of attention ends up being selected and executed.
The probability of selecting the most important shift of attention will
depend on the importance of competing response sets. Suppose that
there are two competing attention shifts with importance weights
between 0 and 10, the probability of selecting a shift of attention
with importance 10 will be higher if the competing shift of attention
has importance 3 than if it has importance 8. Thus, MIS mathematically
describes the selection of a response set from a multitude of
relevant response sets as an increasing function of relative
importance. As the relative importance of a particular shift of attention
increases, that is, as the value of the importance fraction increases,
doing the probability of selection of the attention shift for execution
(cf. model curves; Figure 2 of Grünbaum et al., 2021).

According to MIS, the selection of a response set is a biased com-
petition between response sets represented in LTM. In contrast
hereto, the two-step account of the selection process describes the
process as one in which one and only one response set is activated.
Accordingly, once the cue with the highest reward has been visually
identified, only one shift of attention is relevant. In terms of MIS, this
would correspond to a situation where a response set is selected
without any competition from other response sets. This is the situa-
tion of a single-cue Posner task. Only one cue is associated with a
reward. All other response sets or shifts of attention are given an
importance value close to zero.

MIS (selection with biased competition) and the two-step account
(selection without competition) produce conflicting predictions
about the selection of response sets. Whereas MIS predicts that the
probability of selection of an optimal response set out of a multitude
of possible response sets depends on their relative importance, the
two-step account predicts no such relation. That is, selection without
competition predicts that probability of selection is independent of
relative importance. We can therefore test MIS (selection with biased
competition) against the two-step account (selection without compe-
tition) by looking at whether probability of selection of one attention
shift out of a plurality depends on the relative importance or not. If
the probability of selection of an optimal attention shift is independ-
ent of the subjective importance of other attention shifts, we would
have falsified MIS.

Testing MIS: The Multiple Cue Paradigm

In three experiments using the new multiple cue paradigm, we
were able to show that the selection process is influenced by the
number of relevant possible response sets and that importance oper-
ationalized as associated rewards is a determining factor for the
selection of a response set for execution. As predicted by MIS, the
probability of selecting a response set increased as a function of
its relative importance. The experiments enable us to test the explana-
tory power of MIS by fitting it to the data. We estimate the model
parameters, explore the efficiency of selection, and compare the
rate of processing to the known processing speed for visual
selection.

The multiple cue paradigm is built around the following idea:
Multiple boxes (cue boxes) are associated with a corner where a ran-
dom letter is presented. The general goal of the participant is to col-
lect as many points as possible by correctly reporting a letter from
one and only one of the corners. Which corner gives the highest
reward on a given trial is indicated by a number between zero and
nine occurring in the cue boxes. In the version we present in this
article, four boxes are presented as cue locations in the center of
the screen (see Figure 1). On each trial, the participant has to choose
the corner from which to report a letter, where this selection is influ-
enced by reward values from zero to nine temporarily associated
with each cue box. The crucial part is to manipulate the different
reward values associated with reporting a letter from a specific cor-
nor as well as the time between the cue presentation and the pre-
sentation of the letters (the stimulus onset asynchrony [SOA]). We can
now define optimal performance as the performance that results in
correctly reporting the letter associated with the highest reward
value, and suboptimal performance as when the participant correctly
reports a letter associated with a lower reward value.

The stimulus interval between a reward number presented in a cue
box and a letter presented at an associated corner is such that the par-
ticipant has to quickly shift their attention to the associated corner
in order to be able to discriminate the letter and report it. Thus, each
cue box is associated with a different attention shift that the participant
would have to select for execution in order to be able to execute the
task of discriminating and reporting a letter at the associated corner.
The participant will only be able to report the letter effectively from
the associated corner if they shift their attention immediately to the
associated location. Participants overlearn cue–attention shift associa-
tions in an extensive training period (approx. 30 min), and each cue
box ends up being associated with a separate attention shift. We can
now have a situation where several cues are presented at the same
time. If in each trial, we link each cue box with a reward value for per-
forming the associated task (correctly discriminating and reporting a
letter), the selection of the attention shift should optimally be gov-
erned by the reward values. To ensure that participants encoded and
learned the four cue–attention shift associations separately, we con-
structed a complex cue–target letter location arrangement (see
Figure 1). That is, we made the association between the four cue
boxes and stimulus letters purposely complex to ensure that cue loca-
tions, reward values, and target letters were not encoded as one com-
pound stimulus (Logan & Bundesen, 2003). If participants had been
able to take in the whole display as one unique cue, they would be able to learn single stimulus–response associations. Consequently, despite the presence of several cues, the participants would have been able to learn a response strategy that would be qualitatively like the strategy of participants in the classic Posner single-cue paradigm. Our complex cue–target letter association prevented this.

The central claim of MIS is that relevant attention shifts (response sets) enter a limited capacity competition for execution with reward as a determining factor. The reward value linked to a cue box influences the importance weight of the corresponding attention shift executed in order to report a letter from an associated corner. An attention shift becomes relevant and enters the competition for execution if it has a weight with a value greater than zero. That is, if a cue box is linked to a positive reward value, then the associated attention shift enters a biased competition for execution with other relevant attention shifts, where the probability of winning the competition is influenced by the reward.

The central claim of MIS implies the following two predictions about the performance of participants in the new multiple cue paradigm:

1. Limited processing capacity: If the relevant attention shifts enter a competition for selection governed by a limited processing capacity, as postulated by the importance fraction of Equation 1, then increasing the number of cues linked to a positive reward value (i.e., increasing the number of relevant attention shifts) decreases the overall probability of selecting the optimal attention shift.

2. Biased competition: If the selection of an attention shift for execution is a biased competition influenced by the reward value linked to a cue box, then the probability of selecting an optimal attention shift depends on the relative reward associated with optimal versus suboptimal attention shifts.

Here we define relative reward as the reward of the highest rewarded attention shift divided by the sum of the reward of all competing attention shifts, for example, if two attention shifts with rewards 4 and 1 are competing, the relative reward of the highest rewarded shift equals $4/(4 + 1) = .8$ (cf. Equation 1).

In addition to testing these two predictions derived from MIS, we will apply our model directly to the observed data of the individual participants in the experiments. This enables us to estimate model parameters for each participant including the rate of the selection process and an index of each participant’s ability to set the weights to optimize their performance when multiple cues are rewarded. We show that there is a remarkable difference in the degree to which participants are able to optimize their weight setting.

Contrast the prediction of biased competition derived from MIS with the prediction made by the alternative two-step account of selection. According to the two-step account, there is only one relevant attention shift. This account would interpret the multiple cue paradigm as a sequential task. First, select the highest digit; second, shift attention to report a letter from the associated corner. That is, after identifying the highest digit, there is only one attention shift to be executed. Biased competition might be involved in visually selecting the highest digit, but once this process is complete, the participant can select and execute a shift of attention in order to report the letter from the associated corner without competition from other attention shifts. If we assume that only very few mistakes are made in selecting the highest digit (Blanc-Goldhammer & Cohen, 2014; Finke et al., 2005; Pashler & Badgjo, 1985), execution of the associated attention shift will have a probability close to 1 and will be independent of the reward value associated with the suboptimal performance. The predictions derived from MIS (the biased competition account) and the two-step account of performance in the multiple cue paradigm are visualized in Figure 2. The probabilities are calculated using Equation A5 of the Appendix, assuming a long SOA of 3.0 s and a processing rate of 10 Hz where performance will have asymptoted.

In three experiments, we provide results that support the two predictions of MIS. We thereby provide evidence for the claim that the multiple cue paradigm enables us to study the mechanisms involved in the selection of a response set (here an attention shift) for performance from a plurality of relevant and competing response sets represented in LTM.

Experiment 1: Single and Dual Cues

In Experiment 1, we implemented the multiple cue paradigm in its simplest version. We used only two different types of cue conditions with either one or two rewarded attention shifts. Our aim in Experiment 1 was to find support for the two main predictions derived from MIS: limited processing capacity and biased competition.

Method

Transparency and Openness

We decided to run a relatively small number of participants but in a large number of trials and to do several variations of our new paradigm to replicate the findings. Testing relatively few participants in a larger number of trials provides us with the necessary number of observations per conditions to fit our model to the data of each participant.
This enables us to derive reliable estimates of the parameters of the model for each participant and thus the possibility of comparing these across participants (Ashby et al., 1994). Furthermore, as Oberauer and Lewandowsky (2019) convincingly argue, this strategy for data collection can be preferable in theory-testing research where the theories tested “[…] strongly imply hypotheses, such that disconfirmation of the hypothesis provides evidence against the theory” (Oberauer & Lewandowsky, 2019, p. 1596). For our general analyses, we used Bayesian statistics. Bayesian statistical analyses do not rely on any specification of the data collection in advance (Dienes, 2011; Dienes & Mclatchie, 2018; Kruschke, 2010; Lindley, 1993; Rouder et al., 2009).

We report all rules for data exclusion, all manipulations, and all measures in the study. All statistical analyses reported in this article were done in R 4.2.2 by the R Core Team (2022), using the R packages lme4 1.1.31 by Bates et al. (2015); BayesFactor 0.9.12-4.4 by Morey and Rouder (2012) and Rouder et al. (2017); bayestestR by Makowski et al. (2019); lmerTest 3.1.3 by Kuznetsova et al. (2017); emmeans 1.8.3 by Lenth (2022); and effectsize 0.8.2 by Ben-Shachar et al. (2020) for analyses. The package ggplot2 3.3.3 by Wickham (2016) was used to create all figures. Data collection in all experiments reported in this article took place from 2018 to 2022. All data and analysis scripts from the experiments reported in this article will be made available to download via the Open Science Framework: https://osf.io/ds4ch/.

Participants

Ten participants took part in Experiment 1 (six female, four male, $M_{\text{age}} = 28.5$ years, $SD = 10.9$ years). The participants were naïve to the purpose of the experiment and were recruited via a local participant recruitment network. All participants reported normal or corrected-to-normal vision. Participation in the experiment was compensated with DKK 300 (approximately USD 49) as a baseline payment. Additionally, participants obtained individual amounts of monetary reward worth DKK 123.6–DKK 393.9 ($M = 235.3$ [approximately USD 39], $SD = 78.8$) added to the baseline payment. Participants were tested on 2 consecutive days with a total testing length of approximately 4 hr. The order of the two versions of the experiment (with and without fixation control) was counterbalanced across participants. All participants provided informed consent, and the research was approved by the Local Ethical Review Board at the Department of Psychology, University of Copenhagen, for all experiments reported in this article (protocol number IP-IERB/29092017).

Apparatus and Stimuli

The experiment was conducted using E-Prime (Version 2.0; Psychology Software Tools; W. Schneider et al., 2012) and displayed on a 360 mm × 270 mm CRT monitor with a resolution of 800 × 600 pixels at 100 Hz. Four white boxes sized 20 mm × 20 mm (1.9° × 1.9° of visual angle) were presented against a black background. We call these boxes cue boxes (see Figure 1). The cue boxes were horizontally aligned in a row with 5 mm (0.5°) distance to each other, respectively, and centered around a red fixation cross sized 5 mm × 5 mm (0.5° × $0.5^\circ$) presented at the center of the screen. The cue boxes were either empty or contained a black digit with a value between one and four indicating reward values. The reward values were presented in black capitalized Verdana font with a mean width of 7 mm (0.7°) and mean height of 10 mm (1.0°) and were drawn without replacement. The entire set of stimulus letters consisted of the 26 letters of the alphabet of which four stimulus letters were randomly drawn on a trial-by-trial basis and presented at the four corners of an imaginary rectangle sized 210 mm × 190 mm (20° × 18°) and centered around the fixation cross. The stimulus letters were presented in white capitalized Verdana font with a mean width of 18 mm (1.7°) and mean height of 21 mm (2.0). Pattern masks consisted of gray and white geometric shapes sized 34 mm × 40 mm (3.2° × 3.7°). We used a set of four different pattern masked created by flipping the same pattern both horizontally and vertically. Four pattern masks were drawn randomly with replacement from this set at each trial. The masks were presented at the same locations as the four displayed stimulus letters.

In the version of the experiment with fixation control, an EyeLink 1000 desktop eye tracker (SR Research, 2010) was used with a chin rest. The eye tracker was calibrated at the start of the experiment using a 9-point calibration plus validation display.

Procedure

In both versions of the experiment with and without fixation control, the participant was seated centrally in front of the monitor with a viewing distance of approximately 60 cm and with the keyboard placed on a desk in front of them. The lights in the experiment room were dimmed. The trial began with the presentation of the fixation cross. When properly fixated, the participant initiated the experiment by pressing the space bar on the keyboard. The four cue boxes were then presented followed by the presentation of the four stimulus letters. Five different stimulus onset asynchronies (SOAs) between the onset of the presentation of the cue boxes and the onset of the presentation of the stimulus letters were used: 10, 150, 300, 500, and 1,000 ms. The stimulus letters were visible for 50 ms before they were masked by the four pattern masks presented for 500 ms (see Figure 3). The cue boxes were always visible until the offset of the pattern masks.

In each trial, either one or two cue boxes contained a digit (with values from one to four) while the remaining cue boxes were empty. These digits indicated reward values the participant could collect when reporting the stimulus letter associated with the respective cue box. The associations were as follows starting at the left-most toward the right-most cue box: top-right, top-left, bottom-right, bottom-left stimulus letter (see Figure 1). We will continue to refer to the four letters displayed in a trial as the stimulus letters, and we will refer to the one or two stimulus letter(s) associated with a reward value higher than zero as rewarded letter(s).

The participant was instructed to collect as many reward values as possible while fixating the centered fixation cross. After the presentation of the pattern masks, the participant typed a single letter on the keyboard—encouraged to guess when unsure or unable to encode any of the rewarded letters. The participant’s report was limited to one letter in each trial without a time limitation. Finally, the trial
ended by displaying performance feedback. Three numbers were presented indicating (a) the reward value gained in the trial relative to (b) the maximum possible reward value to gain in the trial, and (c) the currently accumulated monetary reward. The latter number was calculated by dividing the gained reward value by 10 and adding up these numbers throughout the experiment (e.g., when gaining the reward value 4 in the trial, DKK 0.4 [approximately USD 0.05] were added to the currently obtained total monetary reward).

In the version of the experiment with fixation control, we implemented the fixation control by defining an imaginary rectangle of $70 \text{ mm} \times 34 \text{ mm}$ ($6.7^\circ \times 3.3^\circ$) around the central fixation cross. This rectangle captured the four cue boxes but not the other stimuli presented on the screen (i.e., stimulus letters and pattern masks). When the participant’s gaze deviated from the fixation cross outside the imaginary rectangle for fixation control (i.e., approximately 1/3 of the distance from the fixation cross to the locations of the stimulus letters), an error message automatically appeared on the screen saying: “You made an eye movement.” The trial was then categorized as a trial with eye movements. The participant was instructed that despite this message they should complete the current trial by typing a letter on the keyboard and that they also received feedback on their performance, but that potentially collected reward values were not translated and added to the total monetary reward obtained throughout the experiment. The fixation control was only active until the offset of the pattern masks (i.e., before the participant was prompted to report the rewarded letter). See Figure 3 for an illustration of the procedure with and without fixation control.

**Design**

In Experiment 1, the multiple cue paradigm consisted of 10 different cue conditions: four conditions with a single cue (i.e., one box contained a reward value and three remained empty, e.g., 0–0–0–0) and six conditions with all the possible pairs of the four cues (i.e., two boxes contained reward values and two remained empty, e.g., 1–0–2–0). The five different SOAs for each of the 10 cue conditions were run resulted in a total of 50 different experimental conditions. A total of 40 repetitions were run per condition yielding a total of 2,000 trials per participant. Due to an error in the experimental computer program 244 and 203 trials were lost from two of the participants. We therefore decided to run 1,000 additional trials for these two participants and included all of these in the analyses.

The order of the trials was randomized across four blocks of 500 trials each with short breaks in between the blocks to prevent fatigue. Finally, we implemented two fixation control conditions in this experiment: with and without fixation control. Thus, each participant completed 4,000 (or 5,000 trials) in total. Note that in the version
with fixation control, the participants were allowed to move their heads away from the chin rest during the short breaks between the testing blocks. Each new testing block then initiated a new calibration plus validation to ensure the fixation control to be as accurate as possible throughout the experiment.

In both versions with and without fixation control, participants were first familiarized with the paradigm in four practice blocks with increasing difficulty: In the first practice block of 100 trials, only the single-cue conditions were run with an SOA of 1,000 ms, and the stimulus letters were presented for 500 ms before the pattern masks appeared. In the second practice block of 200 trials, all 10 cue conditions were run with an SOA of 1,000 ms, and the stimulus letters were presented for 300 ms. In the third practice block of 200 trials, all 10 cue conditions were run with all five SOAs, and the stimulus letters were presented for 150 ms. The last practice block of 200 trials resembled the testing blocks, that is, 10 cue conditions and five SOAs were used, and the stimulus letters were visible for only 50 ms. We then asked the participants if they felt sufficiently familiar with the multiple cue paradigm or whether they wanted to continue with more training. No participant chose to run more practice trials. Participants spent in total approximately 30 min on practicing the paradigm.

**Results**

We have done all our analyses using Bayes statistics and reporting Bayes factors (BF). Specifically, we use the general notation of BF for Bayesian analyses of variance (BANOVA; Rouder et al., 2017), and BF_{L0} for the likelihood ratio for the one-sided Bayesian t tests. Furthermore, we use the classification of strength of evidence suggested by Jeffreys (1998): A BF of 1 provides no evidence, 1 < BF < 3 anecdotal evidence for the alternative hypothesis, 3 < BF < 10 substantial evidence, 10 < BF < 30 strong evidence, 30 < BF < 100 very strong evidence, and 100 < BF decisive evidence. Correspondingly, the classification for evidence in favor of the null hypothesis is given by values below 1.0, that is, 1/3 < BF < 1 for anecdotal evidence, 1/10 < BF < 1/3 for substantial evidence, etc. We have used the default priors in the BayesFactor package in R (Morey & Rouder, 2022). For Bayesian t tests, the Cauchy prior width is 0.707 and for the BANOVAs, .5 for fixed effects and .1 for random effects. For all our tests, we have run corresponding frequentist versions of the analyses and found essentially the same results.

**Fixation Control**

The total number of trials with eye movements for each participant ranged from 5 to 248 (M = 74.1, SD = 72.0) corresponding to 0%–9% of the trials. We then compared the collected reward values in trials with versus without eye movements using a one-tailed Bayesian t test. We found substantial evidence favoring the null hypothesis rather than the hypothesis of reward values being higher when the participants made eye movements, BF_{L0} = 0.1692. In the other two experiments reported below, eye movements were also infrequent, 0%–5% and 0%–7%, and again there was substantial evidence for the null hypothesis, BF_{L0} = 0.1036 and BF_{L0} = 0.1000, respectively. We excluded all trials with eye movements before we continued to analyze the data in the three experiments.

**Overall Performance**

Figure 4 shows the overall results of Experiment 1. The first row of panels shows the first four conditions (1–4) with a single cue with reward values 1, 2, 3, and 4, respectively. The second and third rows show the remaining six conditions (5–10) with two cues with reward value combinations of 2/1, 3/1, 4/1, 3/2, 4/2, and 4/3, respectively. Each plot shows data from both trials with (triangles) and without fixation control (circles). The probabilities for the response type with zero reward (Z) are calculated as the average probability of reporting one of the two or three nonrewarded letters. The overall pattern in the data reveals that, as expected, performance is low and identical for the three different response types (highest, H; lower, L; and zero reward, Z) at the shortest SOA of 10 ms. At longer SOAs, the differences between performance for the three response types increase. The probability of correctly reporting the highest rewarded letter increases monotonically to the longest SOA of 1,000 ms. In contrast, the probability of reporting one of the nonrewarded letters decreases with SOA. The probability of reporting the lower rewarded letter in the dual-cue conditions is higher than the probability of reporting the nonrewarded letters and increases slowly or stays constant. Finally, the rate of increase in performance is low. The probability of reporting the highest rewarded letter still increases at 500 ms. Comparing performance in the conditions with and without fixation control, the plots indicate that performance was lower with fixation control than without.

We ran separate analyses for the single (1–4) and dual-cue (5–10) conditions. We ran BANOVAs with fixation control, cue condition, response type, and SOA as factors. For the single-cue conditions, we found that the model yielding the strongest support had a BF of 2.938e + 325. The model included main effects of fixation control, response type, and SOA, as well as the two-way interactions between fixation control and response type, fixation control and SOA, and response type and SOA. Finally, the model also included the three-way interaction between fixation control, response type, and SOA. Furthermore, the evidence for the best fitting model relative to the second-best fitting model was decisive, BF = 124.9.

We then analyzed the dual-cue conditions. Here we found that the model with the strongest support had a BF of 1.174e + 546. Once again, the model included main effects of fixation control, response type, and SOA. The interactions included the two-way interactions of fixation control and response type, fixation control and SOA, and response type and SOA, as well as a three-way interaction between fixation control, response type, and SOA. The best model had only anecdotal evidence relative to the second-best model, BF of 1.457. This model differed by not including the three-way interaction. Similarly, the best model had only anecdotal evidence relative to the third-best model, BF of 2.816. Like the second-best model, this model did not include any three-way interactions but neither did it include the two-way interaction between fixation control and SOA.

**Effects of the Number of Cues: Limited Processing Capacity**

Since we found significant effects of fixation control on the overall performance, we decided to run the next analyses separately for with and without fixation control. We continued by comparing performance between the single- and dual-cue conditions to look for
evidence of limited processing capacity. If processing capacity is limited, we expected that the probability of reporting the highest rewarded letter in the dual-cue conditions is lower than in the single-cue conditions where all capacity may be allocated to shifting attention to the highest rewarded letter. Figure 5 shows the probability of reporting the letter cued with the highest reward value as a function of SOA and the number of cues for the trials without (Panel A) and with fixation control (Panel B).
**Effects of the Relative Rewards: Biased Competition**

Since we found no main effect of cue condition nor any significant interaction with SOA in the first overall analyses of all three response types (H, L, and Z), we focused on the report of the highest rewarded letter to investigate whether accuracy of report would change as a function of cue condition for this specific part of the data set. We first analyzed the single-cue conditions (1–4). For the longest exposure durations to maximize the sensitivity assuming that the effect of competition will be most pronounced at the longest SOAs.

**Without Fixation Control.** Figure 6, Panel A shows a plot with accuracy of report of the highest rewarded letter as a function of the reward values in each of the four single-cue conditions when the SOA equaled 500 or 1,000 ms for the trials without fixation control. The analysis yielded anecdotal evidence for no effect of reward value, BF = 0.3609. The estimated slope was low at .004, and the estimate of the intercept was .716. We then ran a BANOVA with only the longest two SOAs of 500 and 1,000 ms. We found decisive evidence for both main effects of the number of cues, BF = 3.380e + 8, and SOA, BF = 1.194e + 7. In addition, we found anecdotal evidence for no interaction between the two, BF = 0.6083. Thus, again performance had not asymptoted at the longest SOA.

**With Fixation Control.** Figure 6 (panel B) shows a plot of the corresponding data with fixation control. The analysis also yielded anecdotal evidence for no effect of reward value, BF = 0.4075. The estimated slope was low at .005, and the estimate of intercept was .566. Thus, both with and without fixation control, we again found support for our prediction that processing capacity was constant across differences in absolute reward values.
We then analyzed the dual-cue conditions (5–10) for the longest SOAs. We ran a Bayesian linear mixed model with relative reward as factor on only the data from SOAs of 500 and 1,000 ms across the dual-cue conditions. Figure 7 shows a plot with accuracy of report of the highest rewarded letter as a function of the relative reward values in each of the dual-cue conditions for trials without (Panel A) and with fixation control (Panel B). By relative reward values, we mean the reward value of the highest valued cue divided by the sum of the reward values for both the highest and the lower valued cue, for example, $4/(4 + 1) = .80$ for Cue 1.

Figure 7
Mean Probability of Reporting the Highest Rewarded Letter as a Function of Relative Reward, With SOAs of 500 and 1,000 ms, in the Dual-Cue Conditions in Experiment 1

Note. Panel A shows without fixation control and Panel B with fixation control. Observed values are indicated by circles and model predictions by crosses. The black solid lines show the results of the linear regressions between relative reward and probability of report. SOA = stimulus onset asynchrony. See the online article for the color version of this figure.
The cues by the participants. The estimate slope and intercept increases systematically with subjective importance attributed to reward associated with the cued attention shifts in line with our central parameters are shown in Tables 2 and 3. Tables of the estimates of all parameters are given in the online supplemental materials.

Table 1

<table>
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<td></td>
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<td>Intercept</td>
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<td>0.716</td>
</tr>
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<tr>
<td>3</td>
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</table>

a The intercept of the dual identical data in Experiment 3 was estimated at a value of .758.

Condition 8 with reward values 4 and 1 (see introductory part and Equation 1).

Without Fixation Control. The analysis yielded decisive evidence for a linear effect of relative reward, BF = 2.657e + 3, indicating that the accuracy of reporting the highest rewarded letter increases systematically with subjective importance attributed to the cues by the participants. The estimate slope and intercept were .480 and .252, respectively (see Figure 7, panel A and Table 1).

With Fixation Control. The analysis yielded very strong evidence for a linear effect of relative reward, BF = 86.81, and the estimate slope and intercept were .301 and .273, respectively (see Figure 7, panel B and Table 1). Thus, both with and without fixation control, we found evidence that relative reward systematically effects performance of reporting the highest rewarded letter. Furthermore, performance is found to be an increasing function of the relative reward associated with the cued attention shifts in line with our central hypothesis (see also Grünbaum et al., 2021).

Model Fitting

To test the explanatory power of MIS, we fitted the model to the data of each participant in Experiment 1. The details of the assumptions and resulting derivations are shown in the Appendix. We derived theoretical probabilities for the different report types as a function of SOA and SOA and used these when fitting the data from each participant separately for trials without and with fixation control. We found maximum likelihood estimates for the parameters, which included: (a) temporal threshold for encoding of the attention shifts, $\tau_c$; (b) total processing capacity for the attention shifts, $C_T$; (c) a selection efficiency index, $\theta$, that determines the weight, $\omega_s$, of an attention shift with reward value, $r$. Specifically, we assume that $\omega_s$ is given by a simple exponential function of $\theta$ and $r$, that is, $\omega_s = \exp(\theta r_{\text{max}})$, where $r_{\text{max}}$ is the maximum reward value given. In the Appendix, we argue that this enables the participant to optimize their performance in the multiple cue paradigm; (d) the weight of the nonrewarded attention shifts, $\omega_c$; (e) visual attention weight for the cues, $w_c$; and (f) visual processing capacity, $C_V$. For ease of comparison, we will report both processing capacity for the attention shifts, $C_T$, and visual processing capacity, $C_V$, in Hz (i.e., in items/s). Estimates of the most central parameters are shown in Tables 2 and 3. Tables of the estimates of all parameters are given in the online supplemental materials.

Table 2

<table>
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<td>.012</td>
</tr>
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</table>

a Since only one exposure duration was used for the target letters, it was difficult to estimate the rate of visual processing. We therefore fixed the maximum value to 200 Hz.

Figure 8 shows exemplary fits for two participants for the trials with fixation control, selected because of their illustratively diverse response profiles. Corresponding plots for all participants in Experiment 1 both for without and with fixation control are shown in the online supplemental materials. In addition, we have plotted the predictions of the model averaged across participants in Figures 4–7 and similarly for the corresponding figures of Experiments 2 and 3. Across all the participants, the model accounted well for the variation in the observed data indicated by $R^2$ -values ranging from .901 to .934 for the trials without fixation control and from .888 to .940 for trials with fixation control (we calculated $R^2$-values using the procedures from Blurton et al., 2020; Nagelkerke, 1991).

When inspecting the plots of the fits for the two participants, the model clearly captures the overall pattern in the data both across cue conditions, SOAs, and for the different response types. The model captures the individual differences between the two participants well. Participant 4 shows a relative high processing rate ($\tau_c = 133.27$). This can be seen in the very small probability of low (L) response types as a function of SOA. On the other hand, selection between the two rewarded cues in the dual-cue conditions is not optimal, that is, the curves for high (H) and low (L) response types as a function of SOA. On the other hand, selection between the two rewarded cues in the dual-cue conditions is not optimal, that is, the curves for high (H) and low (L) reward responses are close to each other. Remarkably, in the dual-cue conditions with pairs of reward values of 2 and 3, and 3 and 4, the participant does not seem to assign any priority between the two cues. This is reflected in a very low estimate of $\theta$ at a value of 0.62. In contrast, Participant 8 has a much slower processing rate ($\tau_c = 0.61$ Hz), but selection is much more efficient, reflected in a very high $\theta$ estimate of 133.27. This can be seen in the very small probability of low (L) reward responses.

All the estimates of the model parameters for with and without fixation control are shown in Tables 2 and 3, respectively. The processing rate of the response set, $C_T$, was much lower compared to the processing rate for visual information, $C_V$, the later being within the range of the rates normally seen in processing of letters (Kyllingsbæk, 2006; Tünnermann et al., 2022). The mean estimates of $C_T$ was 2.86 Hz, and the mean estimate of $C_V$ was around 104 Hz without fixation control, thus more than an order of magnitude in
The corresponding estimates with fixation control were 3.95 and 60.0 Hz for $C_f$ and $C_V$, respectively. Remarkably, the estimates of the selection efficiency, $\theta$, differed markedly between participants reflecting significant individual differences. Apparently, some participants were able to optimize their performance in the task by assigning importance weights that were much higher than the highest monetary reward thus selecting the attention shift with the highest reward across the different dual-cue conditions. In contrast, other participants struggled to prioritize, resulting in selection of attention shifts that were suboptimal. That is, according to the parameter estimates, some participants have a high degree of competition between optimal and suboptimal attention shifts, whereas other participants have much less so. The variation in selection efficiency may be an important reason for why we only found relatively small effects of competition in our analyses across all participants. Probably, the effects were masked by several participants showing very high selection efficiency, thus concealing the competition effects in other participants.

**Discussion**

The results from Experiment 1 clearly support our first prediction of limited processing capacity. We found systematic effects of the number of cued attention shifts when comparing the probabilities of correct report between the single- and dual-cue conditions. In addition, we found an interaction between the number of cues and SOAs so that the difference in performance increased for the longest SOAs compared to the shortest SOAs. The results also support our second prediction of biased competition between attention shifts. Specifically, we found clear evidence for a linear relationship between the relative reward and the probability of correct report of the letter associated with the highest reward in the dual-cue conditions for the two longest SOAs. We explain this result as an increased probability of selecting the attention shift associated with the highest reward when the relative reward increases.

The two-step account would explain the results differently. According to this alternative account, participants first locate the highest digit in a cue box, then shift attention to the associated corner to report a letter. Accordingly, at the second step, the two-step account would predict no systematic difference between one cue and two cue conditions (i.e., no limited processing capacity) and no dependency of responses on relative rewards (i.e., no biased competition). The account must therefore locate the competition effects in the first visual stage of processing, that is, in the visual identification of the highest digit. To test this alternative hypothesis, we ran a control experiment where we presented the exact same displays used in our multiple cue paradigm but while giving the participants a simple visual task. Thus, as displays, we used all 10 cue conditions, that is, the four single-cue conditions with reward values 1, 2, 3, and 4, and six dual-cue conditions with reward values 2/1, 3/1, 4/1, 3/2, 4/2, and 4/3. The task was to report the location of the cue with the highest reward value. In contrast to the multiple cue paradigm, the four cues were post masked to prevent ceiling effects in performance at short exposure durations. Furthermore, instead of empty cue boxes, we presented a digit zero in the cue boxes representing the lack of reward. Thus, all cue boxes contained a digit. We did this to prevent participants from encoding the locations of the cue(s) with positive reward without identifying the cue with the highest reward value. All in all, these changes to the stimulus display would only make it harder to identify the highest rewarded cue compared to Experiments 1–3. Thus, the performance in the control experiment may be treated as a conservative measure of the visual processing of the cues in the multiple cue paradigm.

The results of the control experiment clearly show fast processing and no competition (see Figure 9). We analyzed the results using a two-way BANOVA with report type and SOA as factors. The three levels of report type were (a) highest rewarded cue in the single-cue condition, (b) highest rewarded cue in the dual-cue condition, and (c) lower rewarded cue in the dual-cue condition. We found decisive evidence for a main effect of report type, $BF = 1.317e+383$, strong evidence for a main effect of SOA, $BF = 13.50$, and decisive evidence for an interaction between the two factors, $BF = 2.515e+116$. To investigate whether there was a difference between the single- and dual-cue conditions when the location of the highest digit was reported, we ran a two-way BANOVA for these two report types only. The analysis yielded substantial evidence against an effect of report type, $BF = 0.1465$, decisive evidence for a main effect of SOA, $BF = 5.513e+119$, and strong evidence against an interaction, $BF = 0.0662$. Thus, the analysis shows clear evidence against competition between the cues when the participants decide which one has the highest reward value. We also investigated whether there was any effect of relative reward on reporting the highest rewarded cue location for the two longest SOAs. Running a Bayesian linear mixed model, we found no evidence supporting this ($BF = 0.3395$). Finally, processing was fast. From Figure 9, it appears that performance was at ceiling already after an exposure duration of 80 ms. To test this, we ran a BANOVA for only the two longest SOAs and found decisive evidence for a main effect of report type, $BF = 1.453e+377$, substantial evidence against a main effect of SOA, $BF = 0.1238$, and substantial evidence against an interaction between the two factors, $BF = 0.1046$.

Our interpretation of the results of Experiment 1 was further supported by fitting MIS to the data of the individual participants. The model accounted well for the larger variation of performance between the participants with only a handful of parameters. Noticeable, we found that the rate of processing in the selection of the attention shifts was low, that is, in the order 2–5 Hz, in contrast to the fast processing rates in visual attention found in our control experiment and in previous studies (Kyllingsbæk, 2006; Tünnermann et al., 2022). Furthermore, the distribution of the weights of the different attention shifts varied markedly between participants. Some participants were able to set their weights very efficiently while others were barely able to make any prioritization.

**Table 3**

<table>
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Figure 8
Model Fits to the Data of Two Participants in Experiment 1 With Fixation Control

Note. Response types are indicated by red/dark (highest, H), green/medium (lower, L), black (zero reward, Z), and light-gray (error responses). Circles indicate observed data and solid lines indicate predicted values based on MIS. SOA = stimulus onset asynchrony; MIS = model of intention selection. See the online article for the color version of this figure.
at all. This was reflected in our selection efficiency index, \( \theta \), varying widely between 0.30 and 133.

We were aware that our multiple cue paradigm may be prone to effects of fixation control due to the long SOAs beyond 200 ms (Rayner et al., 1983). Specifically, the capacity effects could be conflated by saccades to the rewarded letters giving the participants the possibility to process the stimulus letters based on fast high accuracy processing in the fovea. We found a general lowering of performance with fixation control. However, we interpret the effect as independent of the selection processes since all our further analyses conditioned on fixation control yielded equivalent results.

The reward values used in Experiment 1 increased in steps of one, that is, digit values of 1, 2, 3, and 4. Next, we asked whether we would be able to find a corresponding pattern of a systematic positive relation between the relative reward values and the probability of reporting rewarded letters when the steps between the reward values are not uniform. In Experiment 2, we investigated this question by using a different set of reward values with nonuniform steps between the reward values.

### Experiment 2: Reward Values 2, 3, 8, and 9

In Experiment 2, we aimed at replicating the results from Experiment 1 while changing the step sizes between the four reward values. Instead of using the digit values 1, 2, 3, and 4, we used the set 2, 3, 8, and 9. The new reward values were chosen so that the difference between the two low values (2 vs. 3) and between the two high values (8 vs. 9) was small while the differences between the two low and the two high values were larger. These changes increase the distance between the smallest and largest relative reward values from \(4/(4 + 3) = .57\) and \(4/(4 + 1) = .80\) in Experiment 1 to \(9/(9 + 8) = .53\) and \(9/(9 + 2) = .82\) in Experiment 2. We did not use 1 as the lowest reward value in Experiment 2 because we presumed that the visual similarity between 1 and 2 would be lower than between 8 and 9. Thus, to minimize this possible confound, we used 2 and 3 as the two lowest reward values.

Our primary aim in Experiment 2 was to find support for both of our predictions: limited processing capacity and biased competition while strengthening the effect of the competition between the attention shifts compared to Experiment 1 due to the changes of step sizes between the reward values.

### Method

#### Participants

Ten participants took part in Experiment 2 (four female, six male, \( M_{\text{age}} = 26.0 \) years, \( SD = 3.0 \) years). Three participants who completed Experiment 1 also took part in this experiment. The remaining participants were recruited via a local participant recruitment network. All participants were naive to the purpose of the experiment. All participants reported normal or corrected-to-normal vision. Participation in this experiment was compensated with DKK 100 (approximately USD 16) as a baseline payment. Additionally, participants obtained individual amounts of monetary reward worth DKK 828.0–DKK 1219.1 \((M = 1,000.5 \text{ [approximately USD 167]}, SD = 146.5)\) added to the baseline payment. Participants were tested on 2 consecutive days with a total testing length of approximately 5 hr.

#### Apparatus, Stimuli, and Procedure

The apparatus, stimuli, and procedure used in this experiment were the same as the ones we used in Experiment 1, with the exception that we changed the digit values of the presented cues to 2, 3, 8, and 9. We used the multiple cue paradigm only with fixation control (see Figure 3).

#### Design

As in Experiment 1, the multiple cue paradigm consisted of 10 different cue conditions in this experiment (i.e., four single-cue conditions, e.g., 0–8–0–0, and six dual-cue conditions, e.g., 2–0–0–8). In contrast to Experiment 1, we decided to add one more SOA of 800 ms and thus resulted with six different SOA conditions (i.e., 10, 150, 300, 500, 800, and 1,000 ms). This resulted in a total of 60 experimental conditions of which a total of 40 repetitions were run, leading to a total of 2,400 experimental trials that each participant completed (excluding practice trials). The order of the trials was randomized across five blocks of 480 trials each. As in Experiment 1, participants started the experiment with practicing. The three participants already familiar with the multiple cue paradigm needed only a short recap.

### Results

Figure 10 shows the overall results of Experiment 2. The first row of panels shows the first four conditions (1–4) with a single cue with reward values 2, 3, 8, and 9, respectively. The second and third rows show the remaining six conditions (5–10) with two cues with reward value combinations of 3/2, 8/2, 9/2, 8/3, 9/3, and 9/8, respectively. The overall pattern in the data is similar to that in Experiment 1. However, including the additional SOA of 800 ms provided extra information, so we were able to estimate the location of the asymptote more precisely. Furthermore, comparing H and L responses in Cue Conditions 5 and 10, having the highest relative
reward values (i.e., 3/2 and 8/9), with the corresponding values in the other dual-cue conditions, it looks as if competition may be stronger compared to the results found in Experiment 1.

We ran a BANOVA with cue condition, response type, and SOA as factors. We ran separate analyses for the single-cue (1–4) and dual-cue conditions (5–10). For the single-cue conditions, the best model, BF = 2.513e + 309, included response type and SOA as main effects, as well as the interaction between response type and SOA. Furthermore, the evidence for the best fitting model relative to the second-best fitting model was decisive, BF = 102.9. In the dual-cue conditions, the best model included both main effects of cue condition, response type, and SOA, as well as the two-way interactions of cue condition and response type, and of response type and SOA, BF = 3.180e + 518. The evidence for the best fitting model relative to the second-best fitting model was decisive, BF = 3.111e + 4.

As in Experiment 1, we compared performance for the highest rewarded letter in the single- and dual-cue conditions to investigate processing capacity limitations and allocation. Figure 11 shows the probability of reporting the letter cued with the highest reward value as a function of SOA and the number of cues. The proportion of correctly reported highest rewarded letters rises as a function of SOA until around 500 ms and asymptotes for the two longest SOAs. We ran a BANOVA with the number of cues and SOA as factors. We found decisive evidence for both main effects, BF = 5.175e + 3 and BF = 2.772e + 206, respectively, as well as for the interaction between the two, BF = 661.4. We interpret the main effect of the number of cues as indicating increased competition between the highest and lower valued attention shifts in the dual-cue conditions compared to the single-cue conditions. The interaction between the number of cues and SOA indicates that the difference in probability of reporting the highest rewarded letter decreased at the longest SOA. This pattern was different than what we found in Experiment 1 where we found evidence for an increase in the difference of performance with longer SOA. We then ran a BANOVA with only the longest SOAs of 500, 800, and...
1,000 ms again with the number of cues and SOA as factors. We found substantial evidence for no main effect of SOA, $BF = 0.1081$, indicating that the performance had asymptoted after 500 ms. In addition, we found a main effect of the number of cues, $BF = 5.889e + 6$, and strong evidence for an interaction between the two, $BF = 20.73$.

Again, we focused our analysis of the single-cue conditions on the data from the longest SOAs of 500, 800, and 1,000 ms to maximize the sensitivity of our analysis. We ran a Bayesian linear mixed model with reward value as factor.

Figure 12 shows a plot with accuracy of report of the highest rewarded letter as a function of reward value in each of the single-cue conditions for the three longest SOAs. The analysis yielded no evidence for or against an effect of reward value, $BF = 0.9362$, but the estimate slope was low at .003. The intercept was estimated at a value of .794, respectively (see Figure 12 and Table 1).

We again ran an additional Bayesian linear mixed model with relative reward as factor on only the data from SOAs 500, 800, and 1,000 ms across the dual-cue conditions. Figure 13 shows a plot with accuracy of report of the highest rewarded letter as a function of the relative reward values in each of the dual-cue conditions. The analysis yielded decisive evidence for a linear effect of relative reward, $BF = 5.091e + 6$, and the estimate slope and intercept were .433 and .440, respectively (see Figure 13 and Table 1). This indicates that the accuracy of reporting the highest rewarded letter increases systematically with subjective importance attributed to the cues by the participants.

Model Fitting

As is Experiment 1, we fitted MIS to the data of each of the participants in Experiment 2. Plots of the fits of each participant are available in the online supplemental materials. Again, the model fitted the data well resulting in $R^2$-values ranging from .883 to .932 (see Table 4). We found low rates of selection for the attention shifts
reflected in estimates of $C_i$ below 10 Hz compared to visual processing capacity, $C_V$, estimated above 50 Hz (Kyllingsbæk, 2006; Tünnermann et al., 2022). The estimates of the selection efficiency index, $\theta$, were on average similar to Experiment 1. However, the variation in $\theta$ in Experiment 2 was much smaller. However, as in the previous experiment, $\theta$ varied significantly between the participants reflecting the individual differences in how the participants were able to select optimally between the rewarded attention shifts.

**Discussion**

In Experiment 2, we replicated the results from our first experiment while changing the step sizes between the four reward values (i.e., 2, 3, 8, 9). As in Experiment 1, we found support for our two predictions. Our first prediction of limited processing capacity of the attention shift selection process was supported by a main effect of the number of cues on the probability of correctly reporting the highest rewarded letter. The results also supported our second prediction of biased competition in the selection process between attention shifts, now with nonuniform steps between the reward values. In the overall analyses of the dual-cue conditions, we found evidence for effects of cue condition and an interaction between cue condition and response type. These indicate that competition varied across the different combinations of reward. Furthermore, the probability of correctly reporting the highest rewarded letter was again systematically increasing as a function of the relative reward associated with the attention shifts. In addition, our results show that performance reaches its maximum after an SOA of 500 ms supporting our interpretations of the results from Experiment 1.

Again, our fits of MIS to the data of Experiment 2 supported our analyses and interpretations. The model accounted well for the participants’ individual data assuming limited processing capacity and competition between the attention shifts dependent on weights derived from an exponential function of the reward associated with the attention shifts. As in Experiment 1, we found significant differences in selection efficiency between the participants.

**Experiment 3: Dual Identical Cues**

In the first two experiments, we have used reward values that were all different from each other. Next, we asked whether our results would generalize to the selection between two attention shifts yielding identical reward, that is, dual identical conditions. Three alternative predictions can be made concerning processing capacity: (a) Given limited processing capacity as evident in the first two experiments: We predict that the probability of correct report in conditions with two identical cues will mirror the report in single-cue conditions in Experiments 1 and 2. (b) Given reduced processing capacity: If two cues generate confusion in the selection, we predict that dual identical conditions will be more difficult than single-cue conditions. (c) Given super processing capacity (cf. Townsend & Ashby, 1983): We predict improved performance in dual identical conditions compared to single-cue conditions. Super capacity may arise due to some kind of visual or more abstract grouping between the two cues or response sets leading to recruitment of extra capacity resources, which would lead to improved performance. A possible mechanism for such an effect may be that not only the two response sets are processed but also a general task rule that combines the two individual response sets (see Grünbaum et al., 2021, p. 10).

**Method**

**Participants**

Ten participants took part in Experiment 3 (four female, six male, $M_{age} = 26.0$ years, $SD = 3.0$ years). They were identical to the participants in Experiment 2. All participants were naïve with respect to the purpose of the study. Contrary to Experiment 1, where we counterbalanced the order of participation in the version with and without fixation control across participants, all participants first completed Experiment 2 before completing Experiment 3. Participation in this experiment was compensated with DKK 300 (approximately USD 49) as a baseline payment. Additionally, participants obtained individual amounts of monetary reward worth DKK 312.5–DKK 588.3 ($M = 500.8$ [approximately USD 83], $SD = 90.6$) added to the baseline payment. Participants were tested on 2 consecutive days with a total testing length of approximately 6 hr.

**Apparatus, Stimuli, and Procedure**

The apparatus, stimuli, and procedure used in Experiment 3 were the same as the ones we used in Experiments 1 and 2. As in Experiment 1, the digit values of the presented cues were 1, 2, 3, and 4. We used the multiple cue paradigm only with fixation control (see Figure 3).

**Design**

As in Experiments 1 and 2, the multiple cue paradigm consisted of four single-cue conditions and six dual-cue conditions. In addition, we added four identical dual-cue conditions in which two digits with the same value were presented inside two cue boxes (1/1, 2/2, 3/3, or 4/4). We thus had a total of 14 cue conditions. As in Experiment 2, the different cue conditions were run with six different SOAs (i.e., 10, 150, 300, 500, 800, and 1,000 ms). We thus resulted with a total of 84 experimental conditions of which a total of 40 repetitions were run, leading to a total of 3,360 experimental trials that each participant completed (excluding practice trials). The order of the trials was randomized across six blocks of 560 trials each. As in Experiments 1 and 2, participants started the experiment with practicing in four practice blocks with increasing difficulty. Since all participants were already familiar with the multiple cue paradigm from previous experiments, the practice time was reduced to approximately 15 min.
Results

Figure 14 shows the overall results of Experiment 3. Panels 1–10 are similar to Experiment 1 (cf. Figure 4). Panels 11–14 are new. They show conditions with two identical cues with reward values 1/1, 2/2, 3/3, and 4/4, respectively. We excluded 0%–7% of the trials due to eye movements. The overall pattern in the data is like that in the previous experiments. Interestingly, the pattern of results in the dual identical cue conditions were very similar to the one in the single-cue conditions. We ran a BANOVA with cue condition, response type, and SOA as factors. We ran separate analyses for the single-cue (1–4), single high (5–10), and dual identical conditions (11–14). For the
single-cue conditions, the best model, $BF = 6.444e + 243$, included response type and SOA as main effects, as well as the interaction between response type and SOA. Furthermore, the evidence for the best fitting model relative to the second-best fitting model was very strong, $BF = 97.35$. Similarly in the single high conditions, we found the best model included main effects of response type and SOA, as well as the two-way interaction between the two, $BF = 8.263e + 460$. However, there was only anecdotal evidence that the performance of the best model was different from the second-best model, $BF = 1.621$. This model included in addition both the main effect of cue condition and the two-way interaction between cue condition and response type. In the dual identical conditions, we found decisive evidence for the best model including main effects of response type and SOA, as well as the two-way interaction between the two, $BF = 3.162e + 260$. There was very strong evidence for this model compared to the second-best model, $BF = 100.7$.

As in Experiments 1 and 2, we compared performance for the highest rewarded letter in the single- and dual-cue conditions but now also distinguishing between the single high (dual-cue condition with nonidentical reward values) and the dual identical conditions to investigate processing capacity limitations and allocation. Figure 15 shows the probability of reporting the highest rewarded letter as a function of SOA and the type of cue condition. The proportion of correctly reported letters rises as a function of SOA until around 500 ms and asymptotes at the two longest SOAs. We fitted a BANOVA with type of cue condition (single-cue, single high, and dual identical conditions) and SOA as factors. We found decisive evidence for both main effects of type of cue condition, $BF = 3.752e + 5$, and of SOA, $BF = 5.552e + 281$. The evidence against the interaction between the two was anecdotal, $BF = 0.5307$. We then ran three additional BANOVAs with the three pairs of type of cue conditions to further investigate the effects of type of cue condition. For the analysis with (a) the single-cue and dual identical conditions, we found anecdotal evidence for no effect of type of cue condition, $BF = 0.5941$. For the other two pairs of (b) single high and dual identical conditions and (c) single-cue and single high conditions, we found decisive, $BF = 5.915e + 5$, and very strong, $BF = 64.98$, evidence for an effect of type of cue condition, respectively.

These findings support our conjectures that (a) processing capacity is again allocated to the lower rewarded attention shift in the single high conditions and (b) all the processing capacity is allocated to both identically rewarded attention shifts in the dual identical conditions. Furthermore, this also suggests limited processing capacity as most plausible hypothesis rather than decreased or super capacity. Had one of these been the case, we would have expected performance in the dual identical conditions (11–14) that would have been systematically lower or higher than performance in the single-cue conditions (1–4).

It is worth noting that, at first sight, the predicted values from the model differ from the observed data. For all SOAs, the model predicts that performance in the dual identical conditions is systematically higher than in the single-cue conditions. The difference between the model predictions of performance in single-cue and dual identical cue conditions can be explained by inspecting the parameter estimates of the model. For shorter SOAs, the difference is mainly due to a higher chance of guessing the highest rewarded letter correctly in the dual identical conditions. For the longer SOAs, the difference is mainly driven by the model predictions for two participants: For Participant 23, the model estimates a relatively high weight on the nonrewarded cues. In the single-cue conditions, this leads to lower performance due to the strong competition from the three nonrewarded cues. By contrast, in the dual identical conditions, the competition from only two nonrewarded cues is weaker. Consequently, the result is higher performance in the dual identical cue conditions. For Participant 43, the model predicts better performance in the dual identical conditions compared to single-cue conditions because the participant allocates little attention to the cues and correspondingly more attention to the letters before the attention shift is encoded (cf. Appendix, Assumptions 4 and 5 and the online supplement materials). Furthermore, this is exacerbated by a very low processing capacity, $C_p$ extending the effect into the longer SOAs. In total, this leads to more instances where a random letter from the display is encoded and reported. The chance of that letter being a rewarded one is obviously larger in the dual identical conditions than the single-cue condition.

We then ran an additional BANOVA for the longest SOAs of 500, 800, and 1,000 ms with type of cue condition and SOA as factors. We found only anecdotal evidence for a main effect of SOA, $BF = 1.808$. This again aligns with performance asymptoting after 500 ms. In addition, the evidence was decisive for a main effect of type of cue condition, $BF = 1.411e + 18$, and the evidence for the interaction between the two was inconclusive, $BF = 1.005$.

We then focused our analysis of the single-cue conditions on the data from the longest SOAs of 500, 800, and 1,000 ms to maximize the sensitivity of our analysis. We ran a Bayesian linear mixed effects model with the number of cues and reward value as factors. Figure 16 shows a plot with accuracy of report of the highest rewarded letter as a function of the reward value in each of the single-cue and dual identical conditions for the three longest SOAs. We found decisive evidence for a difference between single-cue and
dual identical conditions, BF = 3.200e + 3. Using MIS and the model parameter estimates, we can explain this difference as simply an effect of assigning some small weight to the empty cue boxes. In the single-cue conditions, there are three empty cue boxes, whereas the dual identical conditions have only two. The result would be a small increase in competition in the single-cue conditions compared to dual identical conditions. Importantly, we found anecdotal evidence against an additional effect of reward value, BF = 0.4249. The common slope was estimated at a low value of −0.004 and the intercepts at .727 and .758 for the single-cue and dual identical conditions, respectively (see Figure 16 and Table 1).

We again focused on the longest SOAs and ran an additional Bayesian linear mixed model with relative reward as factor on only the data from SOA 500, 800, and 1,000 ms across all dual-cue conditions (5–14). Figure 17 shows a plot with accuracy of report of the single-cue and dual identical conditions as triangles for the observed values. Correspondingly, crosses and stars indicate the predicted values for single and dual identical conditions, respectively. Reward values 1, 2, 3, and 4, and 1/1, 2/2, 3/3, and 4/4 are indicated by black, red/gray, green/silver, and blue/dimgray, respectively. Error bars indicate SE of means for the observed values. The black solid lines show the results of the linear regressions between reward value and probability of report for the single-cue and dual identical conditions, respectively, SOA = stimulus onset asynchrony. See the online article for the color version of this figure.

Figure 16
Mean Probability of Reporting the Highest Rewarded Letter as a Function of Reward Value, With SOAs of 500, 800, and 1,000 ms, in the Single-Cue and Dual Identical Conditions in Experiment 3

Note. Single-cue conditions are shown as circles and dual identical conditions as triangles for the observed values. Correspondingly, crosses and stars indicate the predicted values for single and dual identical conditions, respectively. Reward values 1, 2, 3, and 4, and 1/1, 2/2, 3/3, and 4/4 are indicated by black, red/gray, green/silver, and blue/dimgray, respectively. Error bars indicate SE of means for the observed values. The black solid lines show the results of the linear regressions between reward value and probability of report for the single-cue and dual identical conditions, respectively, SOA = stimulus onset asynchrony. See the online article for the color version of this figure.

Figure 17
Mean Probability of Reporting the Highest Rewarded Letter as a Function of Relative Reward, With SOAs 500, 800, and 1,000 ms, in the Dual-Cue Conditions in Experiment 3

Note. Observed values are indicated by circles for single high conditions and triangles for dual identical conditions. Correspondingly, model predictions are indicated by crosses and stars in the two types of conditions. Individual cue conditions are indicated by the single highest and lower reward value in each of the single high conditions (5–10; red/gray, green/silver, blue/dimgray, yellow/gainsboro, purple/darkgray, and cyan/lightgray circles) and dual identical conditions (11–14; black, red/gray, green/silver, and blue/dimgray triangles). Error bars indicate SE of means of the observed values. The black solid line shows the result of the linear regression between relative reward and probability of report. SOA = stimulus onset asynchrony. See the online article for the color version of this figure.

Table 5
Parameter Estimates From Experiment 3

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Model Fitting

As in the previous experiments, we fitted MIS to the data of each of the participants in Experiment 3. Again, the model fitted the data well resulting in $R^2$-values ranging from .891 to .945 (see Table 5). Again, we find low rates of selection for the attention shifts reflected in mean $C_r$ estimate of 5.22 Hz compared to mean $C_V$ of 57 Hz. The estimates of the selection efficiency index $\theta$ again varied significantly between the participants reflecting the individual differences in how the participants were able to select optimally between the rewarded attention shifts.

Discussion

As in Experiments 1 and 2, the results of Experiment 3 support our central hypothesis of the effect of the associated relative reward on the competitive selection between the cued attention shifts. Again, we found support for our two predictions of limited processing capacity and biased competition. With respect to our first prediction, we tested whether processing capacity in the selection process between attention shifts associated with equal reward was (a) limited, (b) decreased, or (c) enhanced (super capacity, cf. Townsend & Ashby, 1983). As in the first experiments, we found evidence for limited processing capacity by showing a lack of difference in reporting the letter yielding the highest reward in the single-cue conditions (one cue with a reward value) versus performance in the new dual identical conditions (two cues with identical reward values; see Figure 15). Furthermore, the difference between performance in the single-cue and single high conditions (two cues with nonidentical reward values) was replicated from Experiments 1 and 2. Thus, including the dual identical rewarded attention shifts does not change the nature of processing in the attention shift selection process. It should be noted that there may be a slight indication of super capacity for the longest SOAs. It shows up in the small effect in performance as a function of absolute reward values between the two conditions (see Figure 16). Using MIS and its parameter estimates, we explain this effect by a slight increase in competition in the single-cue conditions compared to dual identical conditions (participants assign a small weight to three empty cue boxes compared to two empty cue boxes). In relation to our second prediction that competition between attention shifts is biased, we also replicated our finding of a strong linear relationship between the relative reward and the probability of correct report of the highest rewarded letter. This included the dual identical conditions and thus extended our results from the first two experiments to conditions with multiple identically rewarded attention shifts. Moreover, we found additional strong evidence for biased competition when analyzing the effects of relative reward across the three experiments finding the same effects on performance. These conclusions were all given further support when we fitted MIS to the data from Experiment 3. As in the other two experiments, the model fitted the data well and now extending to situations when cues with identical reward were presented simultaneously.

General Discussion

Our new multiple cue paradigm enabled us to manipulate the process mechanisms behind the selection between a plurality of competing attention shifts. Specifically, we tested two predictions derived from the MIS (Grünbaum et al., 2021): (a) limited processing capacity in the selection between attention shifts and (b) biased competition between attention shifts depending on the relative reward associated with the shifts. The first prediction is supported by results showing that performance of selecting the optimal attention shift depends on the number of rewarded attention shifts. Furthermore, we found no difference in performance of the rewarded attention shift as a function of the absolute reward value in the single-cue conditions. The second prediction is also confirmed. We found that performance of the optimal attention shift was dependent on relative reward in both the dual-cue conditions in all three experiments and the dual identical conditions in Experiment 3. Specifically, we found a linear relationship between relative reward and accuracy of report of the highest rewarded or dual identically rewarded letters in all three experiments. Given the assumption that report of a letter is only possible if attention has been shifted to the relevant location, we have demonstrated a relationship between the relative reward and the selection of an attention shift. Furthermore, the strength indicated by the slope of the linear relation was the same across all experiments.

In addition to the general analyses across participants, we fitted MIS directly to the data of the individual participants. Despite large variations in performance between the participants, we found a remarkable correspondence between the observed data and the predictions of the model in all three experiments. Thus, the model can account for significant individual differences in performance. The rate of processing in the selection of the attention shifts, $C_r$, was found to be less than 10 Hz, and thus much lower than corresponding visual processing rates, which are typically found around 50 Hz (Kyllingsbæk, 2006; Tünnemann et al., 2022). Furthermore, we found that the selection efficiency varied significantly between participants. Some participants were able to set their weights optimally so that the highest rewarded attention shift was almost always selected. In contrast, other participants struggled in their prioritization and were in many cases barely able to discriminate between the cues according to their reward values.

These model findings have important implications for our new multiple cueing paradigm. The group of optimally performing participants assign subjective importance weights to the cues that do not relate linearly to their numerical and monetary value. Basically, if an agent can assign subjective importance weights to response sets in such a way that the difference between an optimal and a suboptimal response set is always very large, irrespective of the actual reward values, the predictions of MIS and the two-step account (no competition) would be indistinguishable (see the introductory part, Equation 1, and Figure 2). The suboptimal response set would enter the competition with such a low weight compared to the optimal response set that it might not be sufficiently different from a situation with only one response set. Future studies should aim to strengthen the effect of competition between response sets. To strengthen the competition effects, we need to ensure that the optimal and the suboptimal response sets in the experimental task have close subjective importance weights also for an ideal rational agent.

Habitual Versus Goal-Directed Processing

With repeated performance of an instrumental action in a recurring context, certain aspects of the instrumental action might end up being controlled by stimulus–response ($S$–$R$) associations triggered by the context. This $S$–$R$ process is often described as habitual (Dolan & Dayan, 2013). To the extent that the control of action is dominated by the habitual $S$–$R$ processing, the instrumental action will no longer be sensitive to beliefs about response–
outcome (R–O) contingencies and rewards (Wood et al., 2022). Psychologists have often claimed that similar automatic mental habits are established by repeated performance of the same mental operation in response to the same cue (James, 1890, Ch 4, Habit). If the cue–attention shift association becomes habitual, the selection should, according to standard theories of habit, no longer be dependent on relative reward.

In the multiple cue paradigm, participants are initially trained in the single-cue condition to associate a specific cue box with a shift of attention to a specific location (see Figure 1). The cue–attention shift (S–R) association is thus extensively trained (for approx. 30 min) and one could expect this process to be habitual. If specific attention shifts become habitually associated with specific cues, then we should expect the selection of attention shifts to be insensitive to rewards. That is, the probability of selecting a target letter should be the same no matter what reward was associated with the cues in our paradigm. Despite extensive training of the S–R aspect of the attention shift, the results appear to demonstrate that attention shifts (at least in the context of the multiple cue paradigm) never become fully habitual. The selection of attention shifts remains flexibly attuned to the rewards (see also Lynn & Shin, 2015). Our results are thus in line with recent results showing the difficulties involved in demonstrating habitual action control in humans (de Wit et al., 2018). To be sure, the absence of effects of habitual S–R processing in the control of attention shifts in the multiple cue paradigm might be due to either an insufficient number of single-cue trials (not enough training of the S–R association) or our focus on the longer SOAs (>500 ms). Recently, Hardwick et al. (2019) demonstrated the effects of habits but only on trials with very extensive training (>4,000 trials) and with short response latencies (300–600 ms). It thus remains a possibility that the competition effects would disappear with more extensive training of single-cue conditions at shorter SOAs (<500 ms).

The standard picture of the relationship between habitual S–R processing and goal-directed R–O processing is that habitual and goal-directed processing are separate and compete for control of action (Dolan & Dayan, 2013; Wood et al., 2022). By contrast, according to an alternative picture of control action, all control action is goal-directed (Hommel & Wiers, 2017). According to this latter proposal, even apparently stimulus-triggered responses and automatic actions are controlled by some flexible representation of outcomes and rewards. Our computational framework, MIS, suggests a third alternative (Grünbaum et al., 2021; for a related proposal, see Buabang et al., 2023). According to MIS, all response sets are represented in LTM as a representation of S–R relations and R–O relations. The S–R relation involves a stimulus component that represents an object or a feature of attention and a response component that represents the sensorimotor consequences of action. The R–O relation involves a propositional component that represents beliefs about outcomes and rewards. The unified set of S–R and R–O representations (in the vocabulary of MIS: the stimulus, response, and propositional components) constitutes what we have called a response set (an attention shift in our paradigm is a response set). Each response set is weighted by its relative subjective importance. With extensive training, the response set can be dominated by its stimulus and response components and its importance weight might be set inflexibly high. With a high match in particular contexts and a high importance weight, the overtrained response set will tend to be selected in those contexts. Thus, according to MIS, habitual actions and goal-directed actions are implemented by the same computational and representational mechanisms. In future studies, it will be important to test this prediction by adjusting the relative importance of nonhabitual response sets until they successfully compete with a more habitual overtrained response set.

The Posner Cuing Paradigm

The new multiple cuing paradigm is structurally similar to the classic Posner cuing paradigm with a number of crucial modifications. The crucial difference is that the participant is presented with multiple endogenous cues that not only indicate the location of the target but also an independently changing reward value. Furthermore, in the version of the multiple cue paradigm used in the present study, important differences to the Posner task are our use of 100% valid cues and the complexity of the cue–target location arrangement.

Let us here discuss some of the few studies that also use multiple cues and associate cues with reward. In the classic Posner task, the participant must detect a single target presented to the left or right. Before the presentation of the target, a cue is presented that indicates the likely location of the target. Two qualitatively different cues are used: externally driven exogenous and internally driven endogenous cues. The Posner paradigm has been used extensively in the attention literature. However, very few studies have investigated the effects of presenting more than one cue at the same time and these have almost exclusively been studying the effects of exogenous cues (Christie et al., 2013; Dukewich & Boehler, 2008; Hu et al., 2014; Klein et al., 2005; Riggo et al., 2000; Wright & Richard, 1996, 2003).

As an exception, Botta and Lupiáñez (2014; Experiment 1) presented two endogenous cues consisting of two digits at fixation. The digit cues indicated probable locations of a later probed target appearing on the perimeter of an imaginary circle around fixation. Their paradigm shares some of the same components as the paradigm used in the present study. However, there are several critical differences. In their paradigm, (a) the number of cues was constant, (b) the two cues were given an equal weight which was constant during the experiment, (c) no reward was explicitly linked to the cues, and (d) the SOA between cues and the letter array was constant. Similarly, Lynn and Shin (2015) presented two peripheral letter cues close to the location of a subsequent target appearing to the left and right. The cue–target SOAs varied at 100, 200, and 500 ms. The letter identity of the cues indicated whether the identification of the target would be rewarded or not. The cue–reward contingencies were kept constant until half-way through the experiment where after they were increased or decreased. Their paradigm differs in two important ways from ours: (a) The number of cues was constant and (b) the cue–reward associations did not change at a trial-by-trial basis.

Given these differences to our multiple cuing paradigm, the experiments by Botta and Lupiáñez (2014) and Lynn and Shin (2015) are unable to critically test the two predictions derived from MIS. In order to study the competition process between multiple shifts of attention, we need an experimental paradigm that allows us to systematically manipulate the number of cues, their associated reward values, and the time between the presentation of the cue and the target. Our new multiple cuing paradigm fulfill these requirements. Future versions of the paradigm should combine these manipulations with a systematic exploration of the probability of valid trials and the complexity of the cue–target associations.
No Competition in Visual Processing of Cues

We could interpret the multiple cue paradigm as having a simple sequential task structure consisting of two steps. First, the participant would locate the highest digit in the display, and second, they would shift their attention to the associated corner. At the second step, the task would be similar to a classic single-cue Posner task. That is, according to this two-step account, there would be no competition between several relevant attention shifts biased by their associated reward values. Accordingly, the two-step account would not predict competition effects at the second step of selecting the shift of attention. The important contrast here is that MIS predicts that the selection is directly dependent on the relative importance of attention shifts, whereas the two-step account predicts that the selection is independent of the relative importance after the location of the highest digit has been determined (see Figure 2).

To explain the competition effects found in Experiments 1–3, the two-step account would have to locate the competition effects at the first step. That is, to the extent that there is any competition involved in the performance of participants in the multiple cue paradigm, the competition should be packed into the first step: visually locating the digit with the highest value. Specifically, it may be argued that competition between the cues when they are processed and encoded visually may explain the effects seen in the experiments. Sometimes participants select (with competition) a digit that is not the highest, and then shift their attention (without competition) to a suboptimal target. This interpretation predicts that effects of competition between the cues should appear when a single versus dual rewarded cues are presented and processed visually.

An alternative but related version of the two-step explanation is that what looks like competition effects is in fact a so-called distance effect in the discrimination of the highest digit (Schwarz & Stein, 1998; Verguts & Van Opstal, 2005). When identifying the highest digit of a pair of single digits, response time is typically longer and performance more error-prone for higher pairs (8 and 9) than for lower pairs (3 and 4). The probability of selecting the wrong number (the digit 8) is therefore higher for the higher pair (8 and 9) than for the lower pair (3 and 4). On trials where participants select the digit 8, they would consequently move their attention to the location of the lowest rewarded target. Given current explanations of distance effects in terms of a primitive analog representation of a number line (Dehaene, 1997, 2001; Reynvoet & Brysbaert, 1999), the digit comparison and discrimination should be a relatively low-level visual process. We should expect the effect to show up in the first stage of processing identified by the two-step account.

To test these alternative hypotheses, we ran a control experiment where we presented the exact same displays used in our multiple cue paradigm while giving the participants a simple visual task. The results of the control experiment clearly showed fast processing and no competition in the first step of visually discriminating the highest digit (see Figure 9). We found no difference in performance between single-cue and dual-cue conditions and no linear relationship between performance and relative reward. Thus, the competition effects shown in Experiments 1–3 cannot be explained as a competition effect or a distance effect in the visual identification of the cues. The effects are best explained as a biased competition between multiple cued attention shifts or response sets, as predicted by MIS. Multiple cues are identified in parallel and activate multiple attention shifts that compete for execution. Notice here the temporal differences between the performance in the visual control task and the multiple cue paradigm. In the control task, participants’ performance reaches ceiling level at around 80 ms. By contrast, in the multiple cue paradigm, participants’ performance asymptotes much later around 500 ms. This temporal difference is supported by our MIS parameter estimates of the visual processing capacity, $C_V$, and the processing capacity for the attention shifts, $C_P$.

Interestingly, this temporal difference is similar to the temporal dynamics seen in the attentional dwell time paradigm where two target stimuli are presented at different locations but with varying SOA (Duncan et al., 1994). However, the theoretical explanations differ. Petersen et al. (2012) (see also Petersen & Vangkilde, 2022) proposed a model of the attentional dwell time where items in visual short-term memory lock processing resources until they are recoded into a reportable format (e.g., auditory code). This process is responsible for the long attentional dwell time. This contrasts with our MIS-based account of the results of the present experiments. In our paradigm, the cues are presented simultaneously, and all processing resources are distributed among the cues in relation to their reward value. Thus, none of the resources are locked. In contrast, the slow time course is due to a much lower processing capacity for this type of selection compared to processing capacity in visual attention. Future versions of the multiple cue paradigm should systematically explore the temporal dynamics and its relation to the attentional dwell time effect.

References


Appendix

Mathematical Assumptions and Derivations of the Model of Intention Selection

Assuming exponential processing, MIS predicts that the probability density and probability distribution functions of encoding component \( k \) from response set \( \chi \) will be given by:

\[
f(t; \chi, k) = \lambda(\chi, k)e^{-\lambda(\chi, k)t}
\]

(A1)

and

\[
F(t; \chi, k) = 1 - e^{-\lambda(\chi, k)t}
\]

(A2)

where \( \lambda(\chi, k) \) is the rate of processing as defined in Equation 1.

Furthermore, we assume that visual processing also follows an exponential distribution but with probability density and probability distribution functions given by:

\[
f(t; \nu) = ve^{-\nu t}
\]

(A3)

and

\[
F(t; \nu) = 1 - e^{-\nu t}
\]

(A4)

where \( \nu \) is the rate of processing of feature \( i \) from a visual object.

To calculate the probability of the different response types in the multiple cue paradigm, we make the following assumptions:

1. For simplicity, we assume that only the stimulus component in MIS is involved in the attentional shift (cf. Logan & Gordon, 2001, p. 396). Thus, we let \( F(t; \chi) \) refer to the probability of encoding the shift of attention, \( \chi \), before time \( \tau \), that is, within the SOA between the presentation of the cues and the target letters.

2. We assume that there is a small temporal threshold, \( \tau_0 \), before the selection race between the attention shifts starts, that is, for processing of the cues. For some participants, the estimated value of \( \tau_0 \) was negative. We interpret this as a result of the cues were unmasked, thus the participants may have been able to use the afterimage of the cues for further processing thereby effectively prolonging the processing time of these (cf. Bundesen et al., 2005; Kyllingsbæk, 2006).

3. Processing capacity of the attention shifts, \( C_I = \sum \lambda(\chi) \), is limited and divided according to their importance weights, \( \omega_i \), where \( r \) is the reward value of the attention shift given by the digit in each cue. As can be seen from Equation 1, the absolute value of the weight is not important, due to the ratio of weights in the equation. Consequently, the weights may be normalized without any loss of generality. We therefore assigned a value of 1.0 to the weight, \( \omega_\chi \), of an attention shift having the smallest positive reward value (see Kyllingsbæk, 2006, p. 125).

4. Before the onset of the trial, we assume that participants divide their visual processing capacity between the cues and the locations of the four target letters. We estimate the attention weight of the cues with parameter, \( w_c \), and again fix the weights of the target letters to 1.0 without any loss of generality. Allocating a certain proportion of the visual capacity to the target letters before the presentations of the cues gives the participants the chance to report a random one of the letters presented even though they were unsuccessful in encoding any of the cues.

5. If the attention shift is selected before the presentation of the target letters, then all visual processing resources, \( C_V = \sum \nu \), are allocated to the target letter of the attention shift.

6. Since we did not vary the exposure duration of the target letters, we fix the perceptual threshold, \( \tau_0 \), to a value of 15 ms, which is typically found in whole report experiments (Kyllingsbæk, 2006). Our estimates of the visual processing capacity, \( C_V \), is based on this assumption.

7. If no attention shift finishes processing and one or more of the four target letters finishes processing, the participant randomly chooses one of these for report.

8. If the participant does not encode any of the target letters, the participant guesses randomly on one of the possible 26 stimulus letters, that is, the probability of guessing correctly is \( P_g = 1/26 \).

From these assumptions we can calculate the probability of attention shift \( \chi \) being selected given SOA \( \tau \):

\[
P(\tau; \chi) = \frac{\lambda(\chi)}{C_I}(1 - e^{-C_I(\tau-\tau_0)})
\]

(A5)

for \( \tau > \tau_0 \), otherwise \( P(\tau; \chi) = 0 \).

Correspondingly, the probability of not encoding any attention shift is given by:

\[
P_0(\tau; \chi) = e^{-C_I(\tau-\tau_0)}
\]

(A6)

for \( \tau > \tau_0 \), otherwise \( P_0(\tau; \chi) = 1 \).

If an attention shift is selected, the probability of encoding the associated target letter is given by:

\[
P(\tau; i) = 1 - e^{-C_V(\tau-\tau_0)}
\]

(A7)

for \( \tau > \tau_0 \), otherwise \( P(\tau; i) = 0 \), where \( C_V \) is the visual processing capacity.

In contrast, the probability of encoding target letter \( i \) when no attention shift has been selected is given by:

\[
P_0(\tau; i) = \frac{1}{n_L} (1 - e^{-C_V w_i(\tau-\tau_0)})
\]

(A8)

for \( \tau > \tau_0 \), otherwise \( P_0(\tau; i) = 0 \), where \( n_L \) is the number of target letters assuming the attentional weight of each letter equals 1.0 relative to the weight of the cues, \( w_c \), as described above.

From the above equations, we can calculate the probability of encoding the target letter \( i \):

\[
P_e(\tau; i) = P(\tau; \chi)P(\tau; i) + P_0(\tau; \chi)P_0(\tau; i)
\]

(A9)

and from that the probability of reporting the target letter \( i \) either by encoding of guessing:

\[
P_i(\tau; i) = P_e(\tau; i) + (1 - P_e(\tau; i))P_g
\]

(A10)

where \( P_g \) is the probability of guessing a letter correctly at random.

(Appendix continues)
Importance Weights

The expected reward across the dual-condition trials in the design in Experiment 1 may be derived as

$$E(R) = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \frac{\omega_i}{\omega_i + \omega_j} + j \frac{\omega_j}{\omega_i + \omega_j}$$

$$= \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \frac{i\omega_i + j\omega_j}{\omega_i + \omega_j}$$

(A11)

where $n$ equals the maximum reward of 4 in a pair of cues with reward values $i$ and $j$ where $i < j$, $\omega_i$ is the weight if the lowest rewarded attention shift, and $\omega_j$ is the weight of the highest rewarded attention shift in the pair.

When examining Equation A11, it becomes clear that $E(R)$ is maximized when $\omega_i \ll \omega_j$. For simplicity, we assume that participants optimized their performance by implementing the following (or a similar) relation between an attention shift with reward value, $r$, and its weight:

$$\omega_r = e^{\theta r / r_{\text{max}}}$$

(A12)

where $\theta$ is an index of selection efficiency, that is, how well the participant is able to select between the possible attention shifts; $r_{\text{max}}$ is the maximal possible reward. We introduce $r_{\text{max}}$ so that we are able to compare values of $\theta$ across experiments.

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