Archives of Scientific Psychology 2017, 5, 1–9
DOI: http://dx.doi.org/10.1037/arc0000030

2169-3269

American Psychological Association

Archives of Scientific Psychology

www.apa.org/pubs/journals/arc

Characterizing the Efficiency of Collaborative Visual Search With Systems Factorial Technology

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ABSTRACT

Professional tasks such as air traffic control and search-and-rescue often involve visual scanning. A novel technology known as gaze-sharing is intended to help people to scan in teams by allowing each of them to see where the other is looking. However, evidence for the helpfulness of shared-gaze displays has been mixed (Brennan, Chen, Dickinson, Neider, & Zelinsky, 2008; Neider, Chen, Dickinson, Brennan, & Zelinsky, 2010). The present study used a novel mathematical analysis to measure the scanning efficiency of teammates linked by the shared-gaze technology in a 2-person visual search-and-consensus task. Results show that shared gaze helped the second searchers find and confirm the target after the first searcher had spotted it, but increased the time for the first searcher to detect the target. Results imply limits on the value of the shared-gaze technology as a way to improve real-world visual search.

SCIENTIFIC ABSTRACT

Shared-gaze technology can improve paired individuals' performance in challenging visual search tasks (Brennan et al., 2008; Neider et al., 2010). To better characterize collaborative search behavior, the current study measured parallel channel efficiency by workload capacity (Townsend & Nozawa, 1995) for pairs of searchers performing a speeded visual search task with or without shared-gaze cursors. Workload capacity was calculated based on the response time of the first searcher to report the target (C_{zOR}) and based on the response time of the second searcher to report it (C_{zAND}). Under shared-gaze conditions, C_{zAND} scores indicated highly efficient performance, but C_{zOR} scores indicated performance losses. Shared-gaze displays reduced the time necessary for the second searcher to confirm a target after the first searcher had found it, but increased the time needed for the first searchers' target detection. Results imply limits on the benefits of shared gaze displays in difficult visual search tasks.

This article was published April 24, 2017.

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This research is supported by ARC Discovery DP150100661 (the Australian Research Council) awarded to Jason S. McCarley. Thanks to Cecil Reynolds, Carrick Williams, and Jim Townsend for helpful comments on an earlier version of the manuscript. Authors also thank Ron Carbonari for programming the experiment and John Powers, Connor Riggs, and Anya Knecht for data collection. The authors have made available for use by others the data that underlie the analyses presented in this paper (see Yamani, Neider, Kramer, & McCarley, 2017), thus allowing replication and potential extensions of this work by qualified researchers. Next users are obligated to involve the data originators in their publication plans, if the originators so desire. For further discussion on this topic, please visit the *Archives of Scientific Psychology* online public forum at http://arcblog.apa.org.

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Keywords: visual search, coordination, shared gaze, workload capacity
Supplemental materials: http://dx.doi.org/10.1037/arc0000030.supp
Data repository: http://dx.doi.org/10.3886/ICPSR36756.v1

Visual scanning is a critical element of many professional tasks, including air traffic control (Remington, Johnston, Ruthruff, Gold, & Romera, 2000), transportation security screening (McCarley, Kramer, Wickens, Vidoni, & Boot, 2004), and industrial inspection (Drury, 1975), and in some cases, may even be a team task (Plant & Stanton, 2016). Unfortunately, search is often slow and imperfect (e.g., McCarley et al., 2004; Wolfe, Horowitz, & Kenner, 2005), and in some contexts may be the limiting factor in the performance of complex, human-machine systems (Yoo & Choi, 2006). Improvements to human search therefore offer the prospect of large gains to safety and efficiency (Leone & Liu, 2011; Yoo & Choi, 2006).

One potential method of improving team search performance comes from the use of *shared-gaze* technology (Brennan, Chen, Dickinson, Neider, & Zelinsky, 2008; Neider, Chen, Dickinson, Brennan, & Zelinsky, 2010; cf. Müller, Helmert, Pannasch, & Velichkovsky, 2012), which provides a method of communication between collaborating searchers. Within a shared-gaze arrangement, two or more searchers view the same scene on different displays. Searchers may be colocated or separated. As they perform their task, the shared-gaze system tracks each searcher's gaze position and cross-projects it onto the other searcher's display (Carletta et al., 2010). Each searcher can therefore know where the other is looking. Ideally, searchers linked through shared-gaze displays will coordinate their attentional behavior to scan the search field more efficiently, locating the target more quickly than either search could alone.

Initial studies gave evidence that collaboration via shared gaze dramatically improved search performance. Brennan and her colleagues (2008) asked pairs of subjects to search for an O among Qs, a task known to produce inefficient performance (Treisman & Souther, 1985). Subjects performed the task alone or in pairs, with paired searchers located in separate rooms and communicating either through speech, shared gaze, or the combination of speech and shared gaze. A trial ended in the paired search conditions as soon as either searcher had reported the target. Response times (RTs) for paired search trials were therefore determined by the first of the two team members to detect the target. Searchers communicating through shared-gaze communication located targets twice as quickly as individual searchers, and surprisingly, even faster than pairs in the shared gaze + speech condition. Eye movement data indicated that the most efficient search teams coordinated their oculomotor behavior by dividing the search field into separate regions for each team member to scan independently.

A follow-up study (Neider et al., 2010) elaborated on these results, asking individual and paired subjects to scan for a sniper in a simulated urban warfare environment. A trial did not end, though, until after one searcher had reported the target and the second had confirmed it. *Search time* was defined as the time needed for the first of two paired searchers to locate a target, and *consensus time* as the additional time needed for the second searcher to confirm the target. Consensus time decreased substantially under shared-gaze conditions, but interestingly, data gave no evidence of a collaborative benefit to search time. The time needed for the first searcher within a shared-gaze pair to locate the target was statistically similar across communication conditions and numerically shortest in the no communication condition, with no evidence of a speed–accuracy trade-off to mask the benefits of communication.

Analyses of mean RTs and oculomotor scanning patterns have thus indicated gaze sharing can allow collaborative searchers to more quickly reach consensus on the location of a target after one searcher has located it, but have produced equivocal evidence that it helps the first searcher in a pair to locate target more quickly. Alternative analytic approaches, though, may provide more informative and sensitive characterization of these effects. Notably, the collaborative search task lends itself to analyses developed for the study of parallel information processing channels within 'black box' mental systems (Townsend & Nozawa, 1995). These analyses offer a theory-motivated method of gauging collaborative search efficiency beyond the analysis of mean RTs.

Systems Factorial Technology and Workload Capacity

Multiple observers searching the same display for a common target constitute a system of parallel, redundant information-processing channels. Collaborative search, in this way, is analogous to the redundant targets task common in cognitive psychology (Egeth, 1966; Miller, 1982; Raab, 1962; Townsend & Nozawa, 1995). Analytic techniques developed for the understanding of redundant processing channels within a single observer would therefore seem applicable to the study of collaborative search teams (cf. Brennan & Enns, 2015). Townsend and Nozawa's (1995) *systems factorial technology* (SFT) offers a methodology for analyzing and characterizing the relationships between redundant processing channels, incorporating insights from a variety of theorists (Grice, Canham, & Gwynne, 1984; Miller, 1982; Mordkoff & Yantis, 1991; Raab, 1962; Schweickert, 1978; Sternberg, 1966). Of most interest here, SFT provides a measure, $C(t)$, of *workload capacity* (Townsend & Eidels, 2011; Townsend & Nozawa, 1995; Wenger & Townsend, 2000), the efficiency with which multiple information processing channels operate concurrently versus in isolation.

Consider a system in which target signals can be presented in isolation to either of two parallel channels or redundantly to both channels, and assume a *first-terminating* or *OR* stopping rule, by which system-level reaction time (RT) is determined by the first channel to finish processing (Colonius & Vorberg, 1994). RTs are typically shorter for redundant-target than for single-target trials (e.g., Ben-David & Algom, 2009; Miller, 1982; Raab, 1962), an effect known as a *redundancy gain*. Capacity limitations modulate the processing times of individual channels as the number of targets varies, and manifest in redundant-target RTs for the system as a whole.

In the simplest model of the redundancy gain, known as the *standard parallel* (Townsend & Eidels, 2011) or *unlimited capacity independent parallel* (UCIP) model (Townsend & Wenger, 2004), redundant targets are processed by parallel, stochastically independent channels, and the processing speed on each of the two channels is the same under redundant-signal conditions as under individual conditions. Because RT is determined by the first of the two channels to finish processing each trial, however, mean RT for redundant-target trials will on average be shorter than that for single-target trials, that is,

$$\mathrm{MIN}(RT_1, RT_2) \leq \mathrm{MEAN}(RT_1, RT_2),$$

where RT_i is a random variable that indicates the RT produced by a target on channel i. The RT gain produced by the standard parallel model is termed *statistical facilitation* (Raab, 1962).

The standard parallel model is termed *unlimited capacity* because it assumes that individual processing channels operate at the same rate under single-target and redundant target channels; adding load to one channel leaves processing speed on the second channel unchanged, an assumption known as *context invariance* (Colonius, 1990; Townsend & Wenger, 2004). If the system is *limited-capacity*, adding load to one channel slows processing on the other, and on average, the individual channels therefore operate more slowly under redundant signal conditions than in isolation. This may imply a resource limitation that limits the ability of channels to operate in parallel (e.g., Wickens, 2002), or alternatively, may indicate inhibition between channels (Eidels, Houpt, Altieri, Pei, & Townsend, 2011). In any of these cases, statistical facilitation may still produce a redundancy gain at the level of the system as a whole, but the benefits of redundant targets will be more modest than in the UCIP model. As capacity limits become more stringent, the system approaches and may even fall below the point of *fixed capacity*, at which redundancy gains are erased. In contrast, if the system is *supercapacity*, redundancy gains are larger than predicted by statistical facilitation alone, indicating some form of information sharing between channels (Eidels et al., 2011; Miller, 1982; Mordkoff & Yantis, 1991). A system may also behave in a limited capacity or supercapacity manner as a result of correlations between the parallel channels' finishing times, violating the UCIP assumption of stochastic independence (Colonius, 1990; Townsend & Wenger, 2004). A positive correlation between the channels finishing times will tend to reduce the size of redundancy gain, engendering limited capacity at the system level. An inverse correlation will tend to increase the size of the redundancy gain, engendering supercapacity at the system level. Therefore, the performance of a redundant channel system may fall short of the UCIP model's predictions either because of a violation of context invariance, or because the finishing times of the parallel channels are positively correlated.

$$C_{OR}(t) = \frac{H_{AB}(t)}{H_A(t) + H_B(t)}, (t) > 0$$

The statistic $C(t)$ is derived from analysis of RT distributions for single- and redundant-target conditions and quantifies system capacity. Following Townsend and Ashby (1978), SFT treats the hazard function $h(t)$ for responses as a measure of the instantaneous capacity expended by the cognitive system, where the hazard function indicates the probability that a response will occur at time t given that it has not yet occurred. The integrated hazard function $H(t)$, which is easily derived from the empirical RT distribution (Wenger & Townsend, 2000), then indicates the total amount of capacity that has been expended up to t. Workload capacity with the OR stopping rule, $C_{OR}(t)$, is defined as the ratio of $H(t)$ for the redundant-target condition to the summed values of $H(t)$ for the two single-target conditions, where subscripts A and B indicate different single-target conditions and A&B indicates the redundant-targets condition (Townsend & Eidels, 2011; Townsend & Nozawa, 1995; Wenger & Townsend, 2000). Values of 1.0 and 0.5, respectively, indicate unlimited and fixed capacity. A value greater than 1.0 therefore indicates super capacity, a value between 1.0 and 0.5 indicates intermediate capacity, and a value less than .5 indicates extremely limited capacity. The capacity coefficient thus provides theory-driven performance benchmarks that shed light on the underlying information processing. For analysis, data can be presented as a function of t to reveal the time course of capacity fluctuations within trials, or can be collapsed over time into a summary measure, C_z (Houpt & Townsend, 2012). Houpt et al. (2014) provide R functions for calculating $C_{OR}(t)$ and C_{Zor}.

More recent work has adapted the capacity coefficient for analysis of two-signal processing performance under an *exhaustive*, or *AND*, stopping rule, by which system-level RT is determined by the last information channel to terminate processing (Townsend & Eidels, 2011; Townsend & Wenger, 2004). Analysis of performance capacity in this case employs the *reverse hazard function* (Chechile, 2003) $K(t)$, which provides the probability that the system has just completed processing at time t given that processing completes at or before t (Townsend & Eidels, 2011). The capacity measure $C_{AND}(t)$ is then defined as the ratio of the reverse hazard function for the redundant-targets condition at time t to the sum of the values for the two single-target conditions, Again, a value of 1.0 indicates unlimited capacity and a value of 0.5 indicates fixed capacity.

$$C_{AND}(t) = \frac{K_A(t) + K_B(t)}{K_{AB}(t)}, (t) > 0$$

As noted, collaborative visual search closely mimics the structure of a standard redundant targets task, with the paired searchers playing the role of parallel redundant processing channels. Capitalizing on this analogy, the current work adopted the statistic $C(t)$ to quantify the efficiency of collaborative search under conditions of shared gaze. Subjects performed a search task either individually or in collaborative pairs linked by shared-gaze cursors (Brennan et al., 2008; Neider et al., 2010), and RT distributions for individual and collaborative conditions were used to calculate capacity measures. Analyses of moment-by-moment levels explored the time course of collaborative search benefits over the course of a trial, and analyses of mean capacity levels examined molar performance differences under individual and collaborative search conditions.

Note that in a standard target search task, a single respondent provides one response each trial, using either an *OR* or an AND stopping rule. To calculate both $C_{OR}(t)$ and $C_{AND}(t)$ therefore requires separate blocks of data collection using the two different stopping rules. In contrast, the current task, like the consensus task used by Neider et al. (2010), produces two responses each trial, one from each of two paired subjects. In effect, the first response provides an RT for the pair, RT_{OR}, based on an *OR* stopping rule, while the second provides an RT, RT_{AND}, based on an AND stopping rule. In the terminology of Neider et al. (2010), RT_{OR} measures the time needed for the search phase of a collaborative search trial, the difference between RT_{OR} and RT_{AND} measures the time needed for the consensus phase, and RT_{AND} measures total search time. The availability of both RTs each trial allowed calculation of $C_{OR}(t)$ and $C_{AND}(t)$, along with the corresponding mean RT values RT_{OR} and RT_{AND}, from a single set of data for each subject pair.

Method

Subjects

Sixteen young adults (10 women, mean age = 24.3 years, SD = 3.6) were recruited from the community of the University of Illinois at Urbana–Champaign. All were screened for normal color perception and normal or corrected-to-normal visual acuity. Subjects were paid for participation.

Apparatus

Stimuli were displayed on two 4′ × 6′ back-projection monitors, resolution of 1,280 × 1,024 pixels, located in separate, quiet rooms. Subjects viewed the displays at a distance of approximately 84 cm, but were free to move as allowed by the eye tracking equipment. Each subject's eye and head movements were tracked at a sampling rate of 60 Hz by an ASL eye tracker (Model 5,000) equipped with a Flock of Birds (Ascention Technology Corporation, Burlington, VT) using goggle-mounted cameras. A fixation was defined as point-of-gaze continuing to remain within an area of 1 visual angle for six or more consecutive samples (100 ms or longer), and fixation duration was defined as the time from the onset of the first sample to the onset of the final sample (Applied Science Laboratory, 2007). A MatLab (Mathworks, Inc.) script running on a central computer, networked to both displays and both eye trackers, controlled stimulus presentation and response collection. Responses were made via a hand-held response box.

Stimuli

Figure 1 presents a sample stimulus display. Each display comprised an array of one letter T and 87 Ls. Stimuli were arranged to form a 10 × 10 grid subtending 43.96° × 39.60° and excluding the 12 positions around the center of the display. The T pointed either leftward or rightward and subtended .89° × .89° of visual angle. The Ls were randomly rotated by 0°–270° in steps of 90° and subtended .89° × .61° each. All letters were drawn in a stroke of .34°. The location of the T was randomly determined each trial. Letters were drawn in white (10.5 cd/m^2) against a gray background (2.84 cd/m^2).

In the collaborative search condition, each subject saw a small gaze cursor on his or her display to represent the gaze position of the paired subject. Gaze cursors were pink Xs, 1.70° × 1.70° in size. In the individual search condition, gaze cursors were absent.

Procedure

Paired subjects were seated in separate quiet rooms without any means of verbal communication. Each trial started with a 1,000-ms blank screen, followed by a 1,000-ms fixation screen. Immediately after the fixation display, the search display appeared and remained visible until both subjects responded. The T was defined as the search target. The subjects' task was to report the orientation of the target within each display, press either the left or right button of a response box to indicate the direction in which the stem of the T pointed as accurately and quickly as possible. They did not receive feedback. The next trial began automatically immediately after the second subject's response.

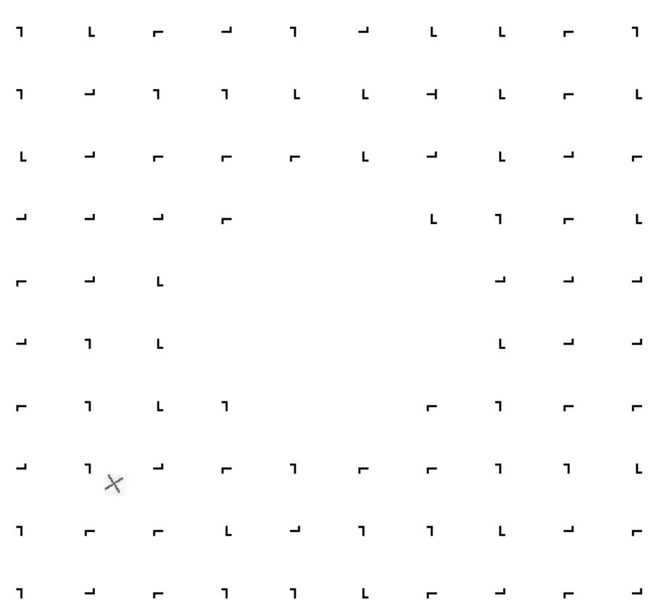

Figure 1. A sample display of the search stimuli with a shared-gaze cursor.

Each subject pair completed one 1-hr session consisting of 10 warm-up trials and four blocks of 100 experimental trials. Each session took approximately 1 hr. Subjects were allowed to rest between blocks.

Results

Error Rates

Error rates were low when averaged across subjects and conditions, $M = 3.2\%$, $SD = 1.2\%$, and did not exceed 7.0% for any single subject. With subject pairs as the unit of analysis, the collaborative condition produced slightly but significantly higher error rates than the individual search condition, arcsin transformed error rates = .13 versus .21, paired-samples $t(7) = 4.19$, 95% confidence interval (CI) [.03, .12]. The following analyses of mean RTs and RT distributions included only trials with correct responses from both subjects in each pair.

Mean RTs

RTs from each subject pair were sorted based on whether they corresponded to the first or second response of a trial, and mean values of RT_{OR} and RT_{AND} were calculated for each subject pair and search condition. Figure 2 presents mean RTs for each condition, with 95% CIs. RT_{OR} was longer for collaborative search than for individual search, mean difference = 0.77 s, 95% CI [.03, 1.51], paired-samples $t(7) = 2.46$. RT_{AND}, however, was shorter for collaborative than for individual search, mean difference = 1.76 s, 95% CI [.47, 3.06], paired-samples $t(7) = 3.23$. Thus, gaze-sharing produced a modest cost to search time (RT_{OR}), but reduced consensus time (RT_{AND}). Analyses of $C(t)$ explored these findings further.

Workload Capacity

Workload capacity coefficients were calculated using the sft package for R (Houpt et al., 2014).

First-terminating (*OR*) responses. Figure 3 presents $C_{OR}(t)$ as a function of time, plotted separately for each subject pair. Only three of eight pairs showed $C_{OR}(t)$ values exceeding the benchmark value of 1.0 for any time t. For the remaining five pairs, $C_{OR}(t)$ values were firmly in the range of intermediate to fixed capacity.

For statistical analysis, $C_{OR}(t)$ values for each pair were converted to the statistic $C_{z\mathrm{OR}}$, which provides a summary measure of workload capacity, collapsed over time. $C_{z\mathrm{OR}}$ values follow a standard normal distribution, with 0 corresponding to unlimited capacity, negative values corresponding to limited capacity, and positive values corresponding to super capacity. Values of $C_{z\mathrm{OR}}$ beyond $\pm$ 1.96 therefore indicate deviations from unlimited capacity that are statistically significant at the level of $\alpha = .05$. Figure 4 presents the value of $C_{z\mathrm{OR}}$ for each pair. The mean value of $C_{z\mathrm{OR}}$ across pairs indicated limited-capacity processing, $M = -3.72$, 95% CI [−6.87, −0.55]. Summary capacity estimates for five of the subject teams were significantly limited (i.e., $C_{z\mathrm{OR}} < -1.96$). For five of the eight pairs, that is, search times for the shared-gaze trials were longer than expected from UCIP processing based on single-searcher RT distributions.

Exhaustive (AND) responses. Figure 5 presents values of $C_{AND}(t)$ as a function of time, plotted separately for each subject pair. Values were generally higher than those of $C_{OR}(t)$, with several teams achieving super capacity values.

Figure 6 presents the summary statistic $C_{z\mathrm{AND}}$ for each subject pair. Like $C_{z\mathrm{OR}}$, $C_{z\mathrm{AND}}$ provides a normalized summary measure of capacity collapsed over time. Across pairs of subjects, $C_{z\mathrm{AND}}$ clearly

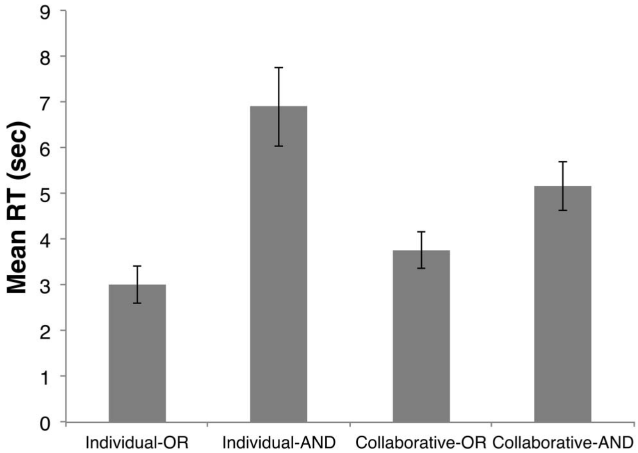

Figure 2. Mean reaction times (RTs) for faster and slower responses in the No-SG (shared gaze) and SG conditions. Error bars represent 95% between-subjects confidence intervals.

exceeded the benchmark value of 0 corresponding to unlimited capacity, falling well within the range of supercapacity, $M = 4.02$, 95% CI [1.65, 6.35]. Summary capacity estimates for four of the subject teams were significantly supercapacity (i.e., $C_{z\mathrm{AND}} > 1.96$).

Oculomotor Behavior

Analyses of eye movements examined the bases of gaze-linked subjects' inefficient visual search. Analysis of subjects' mean fixation durations during the search phase of each trial showed no difference between individual and collaborative search conditions, $M = 178$ ms, 95% CI [170, 187] for individual search, $M = 183$ ms, 95% CI [171, 195] for collaborative search, mean difference $= 5$ ms, 95% CI [-3, 13], paired-samples $t(7) = 1.32$. However, the number of saccades required for the first-responding searcher to locate and report the target was smaller under isolated search conditions, $M = 11.02$ ms, 95% CI [9.97, 12.08], than under collaborative conditions, $M = 13.76$ ms, 95% CI [10.49, 17.03], paired-samples $t(7) = 2.42$.

Collaborative search was thus inefficient primarily because gaze-linked subjects needed more saccades to reach the target. This may reflect either or both a violation of context invariance, compromising the efficiency of attentional guidance, or a violation of stochastic independence between the searchers' scan paths. To test the latter possibility, a further analysis compared searchers' oculomotor behavior under individual and collaborative conditions, adapting a measure of scanpath similarity devised by Mannan, Ruddock, and Wooding (1995). The Mannan statistic measures the spatial proximity of fixations within two sets of scanpaths (Mannan et al., 1995; Henderson, Brockmole, Castelhano, & Mack, 2007), in this case, the scanpaths of paired searchers. Given a pair of scanpaths A and B, the metric quantifies similarity based on the squared distance each fixation in one scanpath and its nearest-neighbor fixation in the other scanpath:

$$D^2 = \frac{n_1 \sum_{j=1}^{n_2} d_{2j}^2 + n_2 \sum_{i=1}^{n_1} d_{1i}^2}{2n_1 n_2 \left(W^2 + h^2\right)},$$

where n_1 and n_2 are the number of fixations for scanpaths A and B, d_{2i} is the distance between the *i*th fixation of scanpath A and its closest fixation in scanpath B, d_{1j} is the distance between the *j*th fixation of scanpath B and its closest fixation in scanpath A, and w and h are the width and height of the search field. Applying this measure to the current data, an index of scanpath similarity for searchers under shared-gaze conditions relative to independent search conditions is provided by the statistic,

$$l_s = 100\left[1 - \frac{D_{SG}}{D_{lnd}}\right],$$

where D_{SG} denotes a distance measure in the shared-gaze condition and D_{Ind} in the individual search condition. Negative values of I_s indicate shared-gaze scanpaths more dissimilar than those in the individual search conditions, and positive values indicate shared-gaze scanpaths more similar than those in the individual search conditions. Although the measure does not take into account information about the temporal order of fixations, it provides a gauge of overlap between regions of the display fixated by the two searchers.

The Mannan similarity metric was calculated using all fixations that ended before the first-responding team member's response. These fixations represent the search phase of each trial. Mean value was positive, $M = 26.47$, 95% CI [15.67, 37.28], suggesting that team members showed more overlap in their scanning under shared gaze conditions than during the baseline, independent search conditions. Across teams, data showed a trend toward an inverse correlation between Mannan scores and Cz_{OR} scores, $r = -0.53$, 95% CI [-0.89, 0.29]; however, the confidence interval on this effect was wide, and overlapped zero.

Discussion

Consistent with the results of Neider et al. (2010), subjects reached faster consensus on the target location each trial when searching in gaze-linked pairs than when searching in isolation, producing smaller values of RT_{AND}. But in contrast to earlier findings (Brennan et al., 2008), gaze-linking not only failed to reduce RT_{OR} (cf. Neider et al., 2010), but produced a cost to it. Analyses of workload capacity reiterated this pattern of costs and benefits: teams collaborating through shared gaze showed supercapacity efficiency as measured by $C_{AND}(t)$ and $C_{z\mathrm{AND}}$, but limited capacity performance as measured by $C_{OR}(t)$ and $C_{z\mathrm{OR}}$. In other words, the time needed for both searchers to find the target was shorter than predicted by the standard parallel model, but the time needed for the first searcher to find the target was longer than predicted.

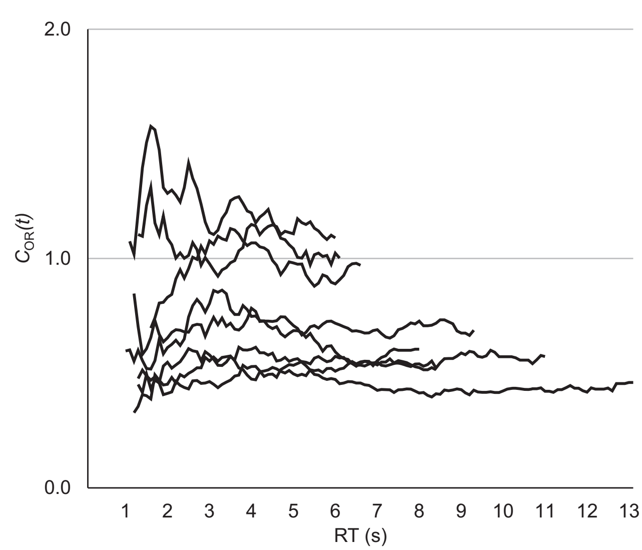

Figure 3. Workload capacity over time under an *OR* stopping rule. Each curve represents the data of a separate team.

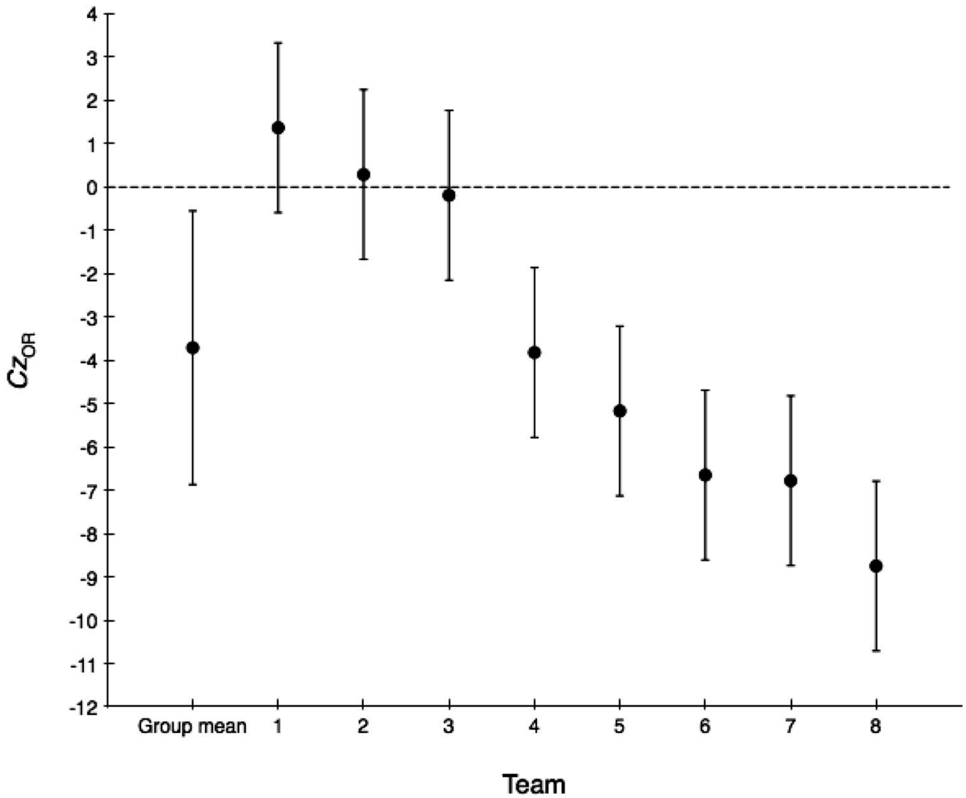

Figure 4. Group mean and individual team values of the summary capacity statistic for first-terminating responses, Cz_{OR}. Error bars indicate 95% confidence intervals (CIs). Values less than 0 denote limited capacity, values greater than 0 denote supercapacity.

As noted earlier, supercapacity implies information sharing between parallel channels (Eidels et al., 2011; Miller, 1982; Mordkoff & Yantis, 1991; Townsend & Wenger, 2004). In the current task, supercapacity levels for AND processing suggest simply that by holding fixation on the target, a searcher could cue his or her partner to the target location. The limited-capacity efficiency observed for *OR* processing is more surprising. Brennan et al. (2008) found substantial benefits of shared gaze to target detection times in an *OR* search task, and although Neider et al. (2010) found no benefits of shared gaze to OR search, neither did they find significant costs. In the present data, teams on average searched more slowly with shared-gaze displays than when working in parallel without shared-gaze cursors. This pattern echoes findings of Müller et al. (2012), who examined the influence of shared gaze on performance in a team puzzle-solving task. Shared-gaze cursors were no more helpful than mouse-controlled cursors in allowing teams to complete their puzzles quickly and accurately, suggesting that gaze cursors were valuable as a way of pointing, but that the visualization of ongoing attentional movements conveyed no further useful information.

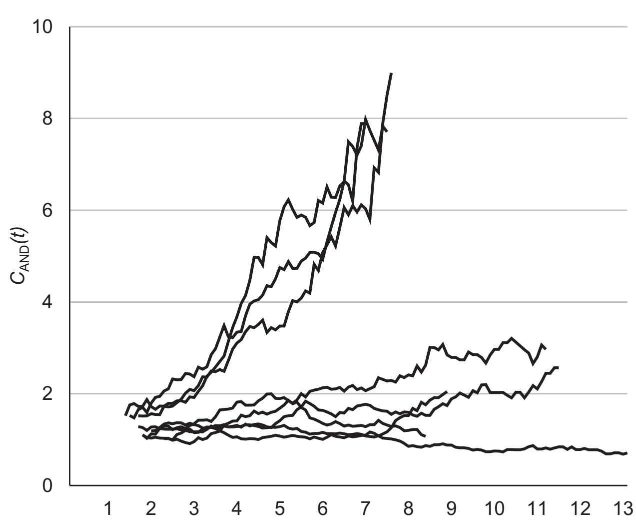

Figure 5. Workload capacity over time under an AND stopping rule. Each curve represents the data of a separate team.

Shared-gaze costs arose at least in part from a tendency for gaze-linked searchers to show more overlap in their oculomotor scanning than independent searchers. In other words, gaze-linking induced a positive correlation in searchers' scanpaths, violating the assumption of stochastically independent channels and reducing workload capacity below the level of the UCIP model's predictions. In contrast, subjects' in Brennan et al.'s (2008) study tended to use a spatial division-of-labor strategy, splitting the search field into halves for the team members to scan separately. Consistent with Brennan et al.'s (2008) findings, workload capacity in the current data trended higher for subjects who showed the least overlap in the scanning. On average, however, the correlations in team members' gaze-linked scanning patterns offset the benefits of parallel redundant channel processing, and no team significantly outperformed the UCIP model. The violation of stochastic independence of course does not rule out a concurrent violation of context invariance. With greater statistical power, for example,

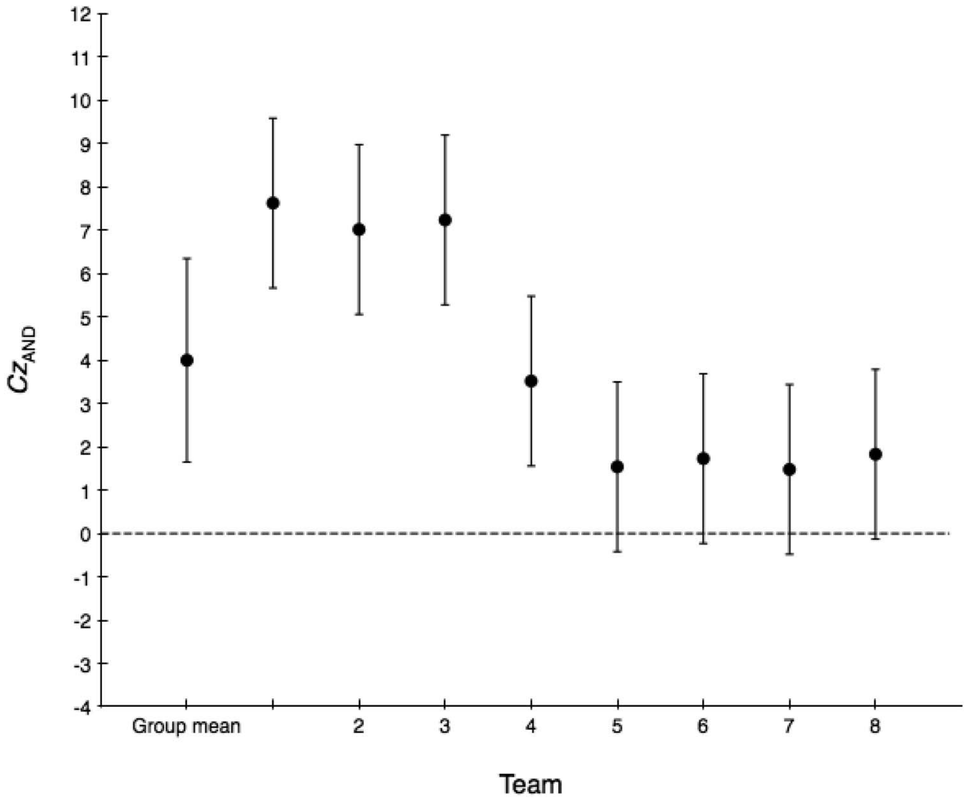

Figure 6. Group mean and individual team values of the summary capacity statistic for second-terminating responses, Cz_{AND}. Error bars indicate 95% confidence intervals (CIs). Values less than 0 denote limited capacity, values greater than 0 denote supercapacity.

data might have revealed a statistically significant increase in fixation durations under collaborative conditions, potentially implying slower perceptual encoding within each dwell fixation. As an alternative, a reduction in the efficiency of attentional guidance or scan path planning may have contributed to the observed pattern of inefficient scanning under collaborative conditions. Clearly, though, limitations in the efficiency of shared gaze search were in large part the result of correlations in the searchers' scan paths.

Alongside earlier work (Brennan et al., 2008; Neider et al., 2010), the current findings suggest that shared-gaze displays are likely to aid performance in tasks that require searchers to reach consensus on the location or identity of a visual target, but that linked searchers may not spontaneously adopt an oculomotor coordination strategy that makes search itself more efficient. These results may indicate simply that instruction or practice is necessary to optimize the efficiency of shared-gaze search. Alternatively, they may imply an inherent tradeoff between the goals of searching for a target and reaching consensus. It is interesting that two studies that have failed to show benefits of shared-gaze search—the current task, and that used by Neider et al. (2010)—both employed an AND stopping rule, that is, they required that both searchers find and respond to a target to end a trial. In contrast, the study that found a benefit of gaze-linking to visual search employed an *OR* task, in which a trial ended as soon as either searcher had responded.

Why might *OR* and AND tasks produce different patterns of shared-gaze influence on search performance? As discussed previously, an efficient strategy for gaze-linked partners to minimize their search time is to divide the search field for scanning, avoiding overlap in their fixations (Brennan et al., 2008). Using this strategy, notably, the partnered searchers in an OR task can decide which regions of the search field each of them will scan, and then can largely ignore one another. To reach a fast consensus in an AND task, however, requires each searcher to monitor to the other's gaze cursor; without noticing that the first searcher has stopped scanning, the second searcher will not know that the target has been found. The task of disambiguating fixations made as part of scanning from fixations intended to communicate the target location, moreover, may well be attention-demanding (Müller et al., 2012). AND tasks thus seem likely to demand sustained, mutual attention between gaze-linked searchers in a way that OR tasks do not. This need for each searcher to continuously and carefully monitor the other's gaze might engender scanpath overlap like that seen in the current data, either by prompting team members to "chase" one another's gaze rather than divide the screen for scanning, or by encouraging an attentional set (Folk, Remington, & Johnston, 1992) that allows the movement of the gaze cursors themselves to attract attention (Ludwig, Ranson, & Gilchrist, 2008) and causes each team member's gaze to gravitate toward the point of the other's fixation. The conflicting demands of avoiding scanning overlap and monitoring each other's may therefore mean that shared-gaze displays can improve either search or consensus-reaching, but not both. This account does not explain why shared-gaze produced a cost to search performance in the current task but a null effect in Neider et al.'s (2010) experiment—additional research will be necessary to determine whether this discrepancy reflects simple error variance, or meaningful contextual differences between the two studies—but it does predict that gaze linking generally will not produce faster search in a task that also demands consensus between team members.

In summary, gaze-linking seems to help paired searchers reach consensus on a target after the one of them has found it, but does not simultaneously help the first searcher find the target faster. These effects are grounded, at least in part, in a tendency for gaze-linked partners to produce overlapping scan paths. By inducing a correlation between the observers' scan patterns, that is, gaze-linking attenuates the redundancy gains that would emerge if searchers worked in parallel and independently, but allows the one searcher to notice more quickly after the first has landed on the target. These effects suggest that the value of shared-gaze in an applied setting will hinge on the nature of the operators' most critical task, search or consensus.

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Received February 16, 2016
Revision received July 21, 2016
Accepted July 21, 2016 ■