

Fanshawe, Thomas R., Phillips, Peter ORCID: <https://orcid.org/0000-0002-7473-6040> , Plumb, Andrew A., Helbren, Emma, Halligan, Steve, Taylor, Stuart A., Gale, Alastair and Mallett, Susan (2016) Do prevalence expectations affect patterns of visual search and decision-making in interpreting CT colonography endoluminal videos? *British Journal of Radiology*, 89 (1060).

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TITLE

Do prevalence expectations affect patterns of visual search and decision-making in interpreting CT colonography endoluminal videos?

SHORT TITLE

Prevalence expectations in CT colonography

TYPE OF MANUSCRIPT

Full Paper

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FUNDING AND ACKNOWLEDGMENTS STATEMENT

This work was supported by the UK National Institute for Health Research (NIHR) under its Program Grants for Applied Research funding scheme (RP-PG-0407-10338). A proportion of

this work was undertaken at University College London and University College London Hospital, which receive a proportion of funding from the NIHR Biomedical Research Centre funding scheme. The views expressed are those of the authors and not necessarily those of the National Health Service, the NIHR, or the Department of Health.

Title:

Do prevalence expectations affect patterns of visual search and decision-making in CT colonography?

Abstract

Objectives: To assess the effect of expected abnormality prevalence on visual search and decision-making in CT Colonography (CTC).

Methods: Thirteen radiologists interpreted endoluminal CTC fly-throughs of the same group of ten patient cases, three times each. Abnormality prevalence was fixed (50%) but readers were told, before viewing each group, that prevalence was either 20%, 50% or 80% in the population from which cases were drawn. Infra-red visual search recording was used.

Readers indicated seeing a polyp by clicking a mouse. Multilevel modelling quantified the effect of expected prevalence on outcomes.

Results: Differences between expected prevalences were not statistically significant for time to first pursuit of the polyp (median 0.5s, each prevalence), pursuit rate when no polyp was on-screen (median $2.7s^{-1}$, each prevalence) or number of mouse clicks (mean 0.75/video (20% prevalence), 0.93 (50%), 0.97 (80%)). There was weak evidence of increased tendency to look outside the central screen area at 80% prevalence, and reduction in positive polyp identifications at 20% prevalence.

Conclusions: This study did not find a large effect of prevalence information on most visual search metrics or polyp identification in CTC. Further research is required to quantify effects at lower prevalences and in relation to secondary outcome measures.

Advances in Knowledge: Prevalence effects in evaluating CTC have not previously been assessed. In this study, providing expected prevalence information did not have a large effect on diagnostic decisions or patterns of visual search.

Keywords

Colon; Colonic Polyps; Colonography, Computed Tomographic; Diagnosis, Computer-Assisted; Visual Perception

Abbreviations and acronyms

CI: Confidence Interval

CTC: CT Colonography

HR: Hazard Ratio

OR: Odds Ratio

REC: Research Ethics Committee

ROI: Region of Interest

Introduction

If we are expecting an event, we are more alert to it and more likely to react when it occurs (1). We might expect that radiologists are more alert to the presence of an abnormality when given an indication that prevalence is particularly high and, conversely, be less alert when the chance of encounter is believed to be low, as in screening.

Interpretation of medical imaging occurs in three environments: the symptomatic population, the asymptomatic/screening population and the research setting. Expected levels of abnormality vary considerably between these settings and between different medical specialties (2). It follows that the effect of varying prevalence of abnormality on image interpretation is crucial to our understanding of how diagnostic accuracy and interpretative performance might change across reporting environments.

In 2011, a systematic review (3) found only three medical imaging studies (4-6) that assessed the impact of experimentally-modified prevalence on reader diagnosis.

Subsequent studies have been published (7-10), but the relationship between prevalence and interpretation accuracy remains unclear. Some studies report increased false negatives or reduced diagnostic confidence at lower prevalence levels, for example for interpretation of pulmonary arteriograms (4), mammograms (8, 11) or ankle trauma radiographs (7). This 'rare target' effect has also been reported in non-clinical scenarios, such as baggage scanning (12, 13) and artificial target search experiments (14). In contrast, in chest radiography the evidence for a prevalence effect on diagnostic accuracy is weaker (5, 9), although two studies that used eye tracking to monitor visual search of experienced readers

suggested a possible association between increased prevalence and the duration and pattern of image scrutiny (10, 15).

Despite increasing use of CT Colonography (CTC) in routine practice, there is little research describing the effect of abnormality prevalence on diagnostic performance (3). This is surprising because CTC is commonly applied across a wide range of expected prevalences, from asymptomatic screenees (16-18) to symptomatic and high-risk patients (19-21).

Establishing the presence or absence of a prevalence effect on reader attention, visual search and diagnostic performance is important both in understanding how CTC should be used in clinical practice and for designing future research studies.

The purpose of this study was to assess the effect of expected abnormality prevalence on visual search and decision-making in CTC.

Materials and Methods

Research Ethics Committee (REC) approval was obtained to record eye tracking data from consenting observers in this prospective study. Institutional Review Board and REC approval was granted to use anonymous CTC data collated in previous studies (22, 23).

Participants and Cases

Thirteen radiologists (readers) were recruited from a UK training hospital over two days in July 2012. All provided written, informed consent. Readers (6/13 male; mean age 32, range 27-36 years) were trainees with 1-7 years experience as a radiologist and at most 50 cases CTC experience.

Ten CTC endoluminal fly-through videos lasting 30s each were generated (EH, PP) with dedicated CTC software on a medical imaging workstation (Vitreia, Vital Images, Minnesota, USA) and exported for viewing. Navigation speed was fixed at approximately 1.5cm/s. Five videos depicted a single colorectal polyp ('true positive', 5-8mm maximal transverse dimension), verified by three radiologists with more than 200 cases experience (23). To counteract recall, cases were excluded if they contained polyps within five seconds navigation of the cecal pole, rectal ampulla or insufflation catheter, or contained other distinctive characteristics, assessed by a radiologist with six years experience (EH). Polyps were onscreen for between 2.4 and 11.1s. The remaining five videos ('true negative') were selected from different sections of colon, containing no polyps, in the same patient group.

The sample size was based on practical considerations: the number of readers available and the number of cases that could be assessed comfortably in one sitting. As the primary outcome measures have not been used before in this context, no power calculation was performed.

Data Collection

The group of ten videos was presented to each reader three times in one sitting, with an optional break between groups. The order of cases was randomized for each reader.

Before viewing each group, readers were told that the videos in that group came from a population with known prevalence of abnormality – 20%, 50% or 80%. The ordering of the three prevalence scenarios was varied between readers using block randomization. Readers were not told that the three groups actually contained the same ten videos repeated three times, and were therefore unaware that the true prevalence was identical (50%) and the declared 20% and 80% prevalence levels were incorrect. Information given to readers was worded as:

“We are going to show you 3 groups of 10 videos in a random order.

Each group is taken from a different population, each with a different prevalence of abnormality.

Before each group we will tell you the population prevalence, either 80%, 50% or 20%.”

Readers were asked to hold a computer mouse throughout and indicate with a click (‘polyp identification’) when they saw a lesion they considered highly likely to represent a real polyp or cancer. Readers were not required to specify polyp location and could not pause, rewind

or re-view videos. They were not told which videos contained polyps and were given no feedback about their performance. Data collection took 20-30 minutes per reader.

Viewing Conditions

Reading was conducted in a quiet room with constant, ambient light. A liquid-crystal display monitor, 1280x1024 pixel resolution, was used (SyncMaster 971P: Samsung, Suwon, South Korea; Fujitsu E19-5: Fujitsu, Tokyo, Japan; 1 pixel=0.29mm). The screen was positioned 60cm in front of the reader. Videos measured 512x512 pixels (14.8x14.8cm), representing a visual angle of 14.1°. Eye position of readers was recorded using a Tobii X50 or X120 eye tracker (Tobii Technology AB, Danderyd, Sweden), sampling at 50Hz or 60Hz respectively, positioned beneath the screen. No head-rest was used. Readers wore glasses or contact lenses as normal. They performed a nine-point calibration procedure prior to data collection and were excluded if this could not be completed. They then viewed a supplemental warm-up video prior to data collection. They were not asked to fixate a particular point before each video.

Data Preparation

Eye position data were prepared for analysis as described elsewhere (24); a summary follows. True positive polyps were approximated using a circular region of interest (ROI), manually overlaid onto each video frame-by-frame by a medical image perception scientist (PP). The center and radius of this ROI were adjusted manually to match the polyp's transition across the screen. Within each frame, the perpendicular distance between the recorded eye position and the edge of the ROI was calculated and used in outcome measures described below. Eye gaze falling within a 50-pixel acceptance radius from the

edge of the ROI was considered to be within high visual acuity. For periods when no polyp was visible, the (x,y)-eye position coordinates were retained for analysis. Coordinates located more than 100 pixels outside the screen area were excluded as recording errors.

Outcome Measures

Eye coordinate data were used to derive three primary and six secondary pre-specified outcomes ('metrics'); see Table 1. Figure 1 shows an example eye tracking trace (distance between eye position and ROI over time) to illustrate metric definitions. Detailed information about metric derivations has been reported previously (25). Metrics reflected three aspects of reader behavior: eye position when a polyp was onscreen; eye position when no polyp was onscreen; and frequency and accuracy of polyp identifications. Primary outcomes were: time to first pursuit of the ROI; pursuit rate in the absence of an ROI; total number of polyp identifications. The 'screen coverage' measure was defined by the proportion of eye gaze falling into three regions: within, above or below a 256x256-pixel square at the center of the screen. 'Any correct identification' and the 'polyp on screen' metrics are defined only for true positive videos. 'Any incorrect identification' is defined only for the period before any polyp appeared, to prevent readers who delayed their decision after seeing a polyp being misclassified as making a false positive identification.

Statistical Analysis

Metrics were analyzed using multilevel modelling, incorporating independent random intercepts for reader and video, including prevalence level as a factor. Effects of prevalence expectation were expressed relative to the true 50% prevalence category. In a planned sensitivity analysis, to test whether results were altered by the order (first, second or third

viewing) in which the prevalence categories were presented, this order was included as an additional factor variable.

Within this multilevel framework, proportional hazards, logistic and Poisson models were used, as appropriate for the data type. As most viewings had at least one missing eye position data point, short missing data runs were imputed, based on the recorded eye coordinates immediately before and after, and adding random measurement error.

Estimates were combined using multiple imputation methods with ten imputations (26).

Cases with more than 50% missing values or more than 50 consecutive missing values were examined individually by two authors (TF, AP) and removed if deemed likely to make the metric calculation highly unreliable. The Electronic Supplementary Material contains more details.

A different approach was adopted only for pursuit rate, which has no generally agreed definition (27). We used the number of pursuits calculated by Tobii Studio version 1.7.2 (50-pixel dispersion, 100ms minimum time threshold) throughout the period when no polyp was onscreen, divided by the duration of this period. Time-points when the Tobii software failed to identify whether a coordinate belonged to any particular pursuit were excluded, and the time denominator adjusted accordingly. Cases with more than 50% missing values of the pursuit classifier were excluded from analysis.

Results are presented as point estimates with 95% confidence intervals (95%CI) and p-values. A 5% significance level was used, unadjusted for multiple testing.

Statistical analysis used Stata 12.1 for Windows (StataCorp, College Station, TX) and R version 3.1.1 (28).

Results

Eye tracking was successful and 389 of the intended 390 viewings were completed. Seven (1.8%) of these were omitted from the analysis of one or more metrics (with the exception of pursuit rate) because patterns of missing data made calculation unreliable. For pursuit rate, 37 (9.5%) of the viewings were excluded.

Table 2 summarizes metrics across all readers within each prevalence scenario. Of the videos that contained a polyp, readers made at least one pursuit of the polyp for 185 of the 190 (97%) viewings with reliable data.

There were no statistically significant differences between expected prevalence levels in any metric relating to visual search while the polyp was visible (Table 3). In each prevalence scenario, readers took approximately half a second on average to direct their gaze to the ROI after the polyp appeared (hazard ratio (HR) 1.32 (95%CI 0.95 to 1.93, $p=0.14$) for 20% versus 50% prevalence; HR 0.95 (95%CI 0.64 to 1.40, $p=0.79$) for 80% versus 50% expected prevalence; Tables 2 & 3, Figure 3). Average Total assessment time span, Assessment pursuit time and Assessment pursuit rate were also similar in the three prevalence scenarios (Tables 2 & 3).

During the period when the polyp was not on screen, the average pursuit rate was approximately 2.7 pursuits per second at each of the three prevalence levels (Table 2), with

no statistically significant differences (Table 3). There was a tendency for readers' gaze to fall inside the central region of the screen less often at the 80% prevalence level than at the 50% prevalence level (odds ratio (OR) 0.82 (95%CI 0.72 to 0.95, $p=0.008$), Table 3), with a concomitant increase in the upper region. This effect however was small, with on average 82% of gaze points falling in the central region at 80% prevalence compared to 84% at 50% prevalence (Table 2).

There were no statistically significant differences with respect to expected prevalence regarding the total number of identifications (Table 3). As expected, the average number of identifications was higher for videos that contained polyps than for those that did not (1.3 versus 0.4, Table 2). The sensitivity, or probability of a polyp being correctly identified, was higher at 50% prevalence (86%) than at 20% prevalence (71%). This difference was statistically significant ($p=0.01$, Table 3) but the trend did not persist at the 80% prevalence level (75%). This metric was subject to an extremely high case-specific effect (Figure 4), as in three videos (1, 2 and 4) almost every reader identified the polyp at each prevalence level; the other two videos (3 and 5), for which the polyp was superficially more difficult to identify, are therefore likely primarily responsible for the differences in rates of correct identification.

The probability of an incorrect identification ('false positive') ranged from 30% at 20% prevalence to 39% at 80% prevalence; this difference was also not statistically significant (Table 3). On average, incorrect identifications occurred with similar frequency for videos that contained no polyps and for videos that contained polyps during periods when the polyp was not visible, although there was considerable variability between cases (Figure 4).

Some false positive features were identified with a mouse click by several readers (e.g. Case 3 at 5 seconds, Figures 4 and 5).

In sensitivity analysis, including as an extra factor variable the order in which the prevalence scenarios were presented did not affect the prevalence effect sizes shown in Table 3.

Discussion

This study investigated the effect on visual search and decision-making for CTC of providing readers with substantially different expectations of the likely prevalence of abnormality in the population from which cases were drawn. We did not demonstrate a strong link between prevalence expectation and the pattern of search or decision-making.

Our conclusion differs from those of several studies using scenarios other than CTC that found increased false negative rate at lower prevalence levels (8, 12-14). Our study showed a statistically significant increase in the proportion of polyp identifications between 20% and 50% expected prevalence, but for three reasons this finding should be treated cautiously. First, it did not extend to the highest prevalence level, for which the proportion was similar to that at 20%, and a non-monotonic relationship seems implausible. Second, the effect was driven by an increased true positive rate in just two of the five cases with polyps: a consistent increase across all cases, which would have provided more convincing evidence, was not observed. Third, this was just one of several secondary analyses performed, and so it may be a chance result.

The existence of a prevalence effect is not a universal finding in image interpretation studies. For example, Gur et al. (5) found that varying prevalence levels between 2%-21% did not affect the diagnostic accuracy of chest radiograph assessment. Likewise, we did not find a prevalence effect for our three primary outcomes, which were chosen to represent visual search and decision-making. Modality may therefore be an important determinant of prevalence effects.

We have shown previously that time to first pursuit of the polyp changes with reader experience and the presence of a computer-aided detection marker (29, 30); in the present study this metric was unchanged across prevalence scenarios. When no polyp was visible, readers tended to spend more time, proportionally, looking at peripheral screen regions in the 80% prevalence condition, but this effect is small and is not supported by changes in other visual search metrics. However, the finding requires further investigation as our measure is based on a simple square at the center of the screen area, which may not adequately capture gaze narrowing effects.

We used a common set of cases for each of the prevalence conditions to directly observe the effect of disclosing different prevalence information, as opposed to the effect of the true case-mix. Lau et al. (31) claim that the latter may have a larger effect on decision-making, but testing this was not our objective. Indeed, it would have been infeasible for readers to make an assessment of the true underlying prevalence within a realistic time-frame. It is possible that some readers realized that they had viewed videos more than once, but this is unlikely to have a major effect on our findings: the order in which the prevalence conditions were presented was determined randomly, and this order was not

strongly associated with outcomes. Enabling all cases to be viewed with comfort in a single sitting was an important practical consideration in our choice of the number of cases used. Despite the number of cases being moderately small, repeated viewings of the same case under different prevalence conditions enabled quantities of interest to be estimated with acceptable precision.

Future studies should assess further the possibility of a threshold effect in CTC. It is possible that the expected prevalence level needs to be lower than 20% for an effect to be visible, as is usually the case in everyday clinical practice except in very high-risk patient groups such as those examined following a positive fecal occult blood test (21). Evans et al. (8) found a marked reduction in sensitivity for breast cancer diagnosis using mammography during screening when the prevalence was extremely low (0.3%). Whether a similar effect applies to CTC remains unknown. Additionally, prevalence effects may vary according to the ease of visualization and identification of the cases chosen.

This study has limitations. This study was exploratory in nature, and therefore we may not have used enough cases for subtler prevalence effects to be detected. Endoluminal fly-through view was presented in automatic mode only, so readers could not adjust navigation speed as in usual practice. We were therefore unable to assess the effect of prevalence on the time the reader would spend scrutinizing each video; from laboratory experiments and some clinical studies, there is evidence that assessment time is affected by prevalence in static viewing modes (15, 32). Mouse clicks are not synonymous with definitive decisions about the presence of polyps, and thus can only be regarded as proxy measures of diagnostic accuracy. Readers were not asked to identify polyp locations and so, even with

eye tracking data, it is impossible to state with certainty the cause of any particular click. Readers were inexperienced in CTC, and so our findings are not directly generalizable to experienced radiologists using CTC in day-to-day clinical practice. Finally, we did not assess the effect of providing information about the spectrum of disease severity, since readers received prevalence information alone.

In summary, CTC readers were provided with different estimates of the prevalence of abnormalities from which cases were drawn, and study results did not demonstrate a strong link between prevalence information and the pattern of visual search or decision-making. Further research should investigate effects at lower prevalence levels, such as might be present in asymptomatic populations.

Acknowledgements

This work was supported by the UK National Institute for Health Research (NIHR) under its Program Grants for Applied Research funding scheme (RP-PG-0407-10338). A proportion of this work was undertaken at University College London and University College London Hospital, which receive a proportion of funding from the NIHR Biomedical Research Centre funding scheme. The views expressed are those of the authors and not necessarily those of the National Health Service, the NIHR, or the Department of Health.

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Group	Name	Definition
Polyp on screen	Time to first pursuit*	Time between appearance of polyp (A) and start of first pursuit of polyp (B)
	Total assessment time span	Time between start of first pursuit of polyp (B) and polyp identification (E)
	Assessment pursuit time	Cumulative time in pursuit of polyp before polyp identification (B to C and D to E), expressed as a proportion of the total time the polyp was visible (A to G)
	Assessment pursuit rate	Number of separate pursuits of polyp before polyp identification, divided by the total time the polyp was visible before polyp identification (A to E)
Polyp off screen	Pursuit rate*	Number of distinct eye pursuits, divided by the total time when the polyp was off screen
	Screen coverage	Proportion of eye coordinates falling in to each of three regions of the screen display, 'upper', 'central' and 'lower'; see Figure 2
Polyp identification	Total number of identifications*	Number of identifications recorded over whole video
	Any correct identification	Binary indicator of whether an identification occurred while the polyp was visible (a reaction time of 0.5s after the polyp left the screen was allowed)
	Any incorrect identification	Binary indicator of whether an identification occurred before the polyp was visible (or at any time, for true negative videos)

* primary outcome

Table 1: Metric definitions. The identifying letters A, B, etc. refer to time points indicated in Figure 1.

Metric	20% prevalence	50% prevalence	80% prevalence
At least one pursuit of polyp	63/63 (100%)	61/64 (95%)	61/63 (97%)
Immediate pursuit	5/63 (8%)	4/64 (6%)	10/63 (16%)
Time to first pursuit (s) *	0.45 [0.26, 0.65]	0.52 [0.28, 0.82]	0.52 [0.37, 0.95]
Total assessment time span (s) *	2.45 [1.33, 5.96]	1.75 [1.00, 3.49]	2.19 [1.15, 5.76]
Assessment pursuit time (%)	24% [14%, 34%]	21% [13%, 33%]	18% [12%, 33%]
Assessment pursuit rate (s ⁻¹)	0.59 [0.42, 0.79]	0.56 [0.42, 0.83]	0.69 [0.45, 0.85]
Pursuit rate (s ⁻¹)	2.69 [2.19, 3.09]	2.67 [2.23, 3.02]	2.71 [2.26, 3.11]
Screen coverage			
Upper	6% [3%, 13%]	7% [5%, 12%]	9% [5%, 15%]
Central	87% [77%, 92%]	84% [77%, 90%]	82% [73%, 89%]
Lower	7% [4%, 12%]	8% [5%, 13%]	8% [6%, 13%]
Total number of identifications	0.75 (0.82)	0.93 (0.90)	0.97 (1.07)
Videos with polyps	1.17 (0.80)	1.38 (0.90)	1.43 (1.16)
Videos without polyps	0.34 (0.59)	0.49 (0.66)	0.51 (0.73)
Any correct identification	46/65 (71%)	55/64 (86%)	49/65 (75%)
Any incorrect identification	39/130 (30%)	48/129 (37%)	51/130 (39%)
Videos with polyps	21/65 (32%)	22/64 (34%)	25/65 (38%)
Videos without polyps	18/65 (28%)	26/65 (40%)	26/65 (40%)

Table 2: Summary of metrics by prevalence level (number (%) or median [inter-quartile range] except for total number of identifications: mean (standard deviation)).

* Kaplan-Meier estimate, calculated without allowing for clustering, excluding viewings with immediate pursuit

Metric	Measure	20% versus 50% prevalence		80% versus 50% prevalence	
		Effect size [95%CI]	p	Effect size [95%CI]	p
Time to first pursuit	HR	1.32 [0.95, 1.93]	0.14	0.95 [0.64, 1.40]	0.79
Total assessment time span	HR	0.74 [0.50, 1.12]	0.15	0.83 [0.56, 1.24]	0.37
Assessment pursuit time	OR	1.27 [0.87, 1.84]	0.22	0.90 [0.62, 1.32]	0.60
Assessment pursuit rate	RR	0.91 [0.70, 1.18]	0.47	1.07 [0.83, 1.37]	0.60
Pursuit rate	RR	1.01 [0.98, 1.05]	0.39	1.03 [1.00, 1.07]	0.06
Screen coverage					
Upper	OR	0.93 [0.78, 1.12]	0.45	1.28 [1.07, 1.53]	0.007
Central	OR	1.06 [0.92, 1.23]	0.39	0.82 [0.72, 0.95]	0.008
Lower	OR	0.96 [0.81, 1.13]	0.63	1.11 [0.94, 1.31]	0.22
Total number of identifications	RR	0.81 [0.62, 1.06]	0.12	1.04 [0.81, 1.34]	0.75
Any correct identification	OR	0.24 [0.08, 0.73]	0.01	0.37 [0.12, 1.11]	0.08
Any incorrect identification	OR	0.66 [0.37, 1.19]	0.17	1.11 [0.63, 1.97]	0.71
Videos with polyps	OR	0.86 [0.35, 2.11]	0.75	1.29 [0.54, 3.10]	0.57
Videos without polyps	OR	0.53 [0.24, 1.17]	0.11	1.00 [0.47, 2.13]	1.00

Table 3: Comparison of metrics between prevalence levels: hazard ratio (HR), odds ratio (OR) or rate ratio (RR), as appropriate, with 95%CI and p-value.

Table and Figure Legends

Table 1: Metric definitions. The identifying letters A, B, etc. refer to time points indicated in Figure 1.

Table 2: Summary of metrics by prevalence level (number (%) or median [inter-quartile range] except for total number of identifications: mean (standard deviation)).

Table 3: Comparison of metrics between prevalence levels: hazard ratio (HR), odds ratio (OR) or rate ratio (RR), as appropriate, with 95%CI and p-value.

Figure 1: Illustration of distance between eye position and polyp (edge of ROI) over time for a single video viewing. Letters used in explanation of metric definitions, A: polyp becomes visible, B to C: first eye pursuit of ROI, D to F: second eye pursuit of ROI, E: polyp identification (indicated by dotted line), G: polyp disappears from view. Note short periods of missing data at 17.7 and 19.7 seconds. The horizontal line at distance 0 represents the edge of the ROI, and the horizontal line at distance 50 pixels the high visual acuity region within which eye pursuits of the ROI may occur.

Figure 2: Illustration of the screen coverage metric, showing the division of the screen area into Upper, Central and Lower regions (dashed lines). The Central region occupies a 256x256-pixel square at the center of the 512x512-pixel screen area (solid line). An additional 100-pixel margin (shown by the outer bounding box) was allowed for gaze points measured outside the screen area; this was incorporated into the Upper or Lower region, as appropriate. Superimposed is the pattern of gaze over the entire video duration for a single

reader (Reader 11) viewing the same case (Case 3) under different prevalence conditions: 20% (left panel), 50% (middle panel) and 80% (right panel).

Figure 3: Kaplan-Meier curves showing time to first pursuit in the three prevalence conditions. The vertical axis shows the proportion of viewings for which a pursuit has occurred prior to the times shown on the horizontal axis. Below the plot, the number of viewings per group for which a pursuit has not yet occurred is shown.

Figure 4: Time points within each video at which polyp identifications occurred. Prevalence conditions are indicated by different colors. Cases that contain a polyp are labelled 1 to 5, and the red bar indicates the period during which the polyp was visible on the screen. Cases with no polyps are labelled 6 to 10.

Figure 5: Screen-capture from one of the displayed videos (Case 3, at around 5 seconds) showing a feature provoking a false-positive, in this case a mildly bulbous but normal fold (arrow).

Appendix A

Additional Details of Statistical Analysis

The multilevel model used for the primary analysis incorporated independent random intercepts for reader and video and included prevalence level as a factor. If the standard deviation of either of the random effect distributions was estimated to be zero, the model was refitted with this random effect term removed to ensure that the estimates of the fixed effects and their standard errors were stable. A table of estimated standard deviations of the random effects is included as Supplemental Material.

The exact form of the model depended on the data type. A proportional hazards model was used for two metrics (Time to first pursuit and Total assessment time span), as these are time-to-event variables, measuring periods of time until an identification of the polyp occurs. Only the first 'event' (pursuit of ROI, or polyp identification) was used for these variables: any events occurring subsequently, such as a duplicate identification of the same polyp or to indicate a different polyp, were discarded in the analysis of these two metrics. Cases for which no event occurred were regarded as censored at the time the polyp left the screen. Events that occurred at time zero, such as a reader's gaze falling within the ROI at the instant the polyp became visible, were excluded from the analysis as they do not contribute to the likelihood under the standard proportional hazards model and such events are assumed to have occurred only because of chance. The proportional hazards assumption was checked graphically using a log-log survival plot. Results are presented as hazard ratios.

Logistic models were used for variables that were binary (Screen coverage, which was analyzed as three separate binary categories, Any correct identification and Any incorrect identification). The metric 'Any incorrect identification' was analyzed separately for all videos, for videos with polyps and for videos without polyps. This analysis was pre-specified. The metric 'Assessment pursuit time', which is expressed as a proportion of the time the polyp is visible, was also analyzed using a logistic model after first logit-transforming the variable (a small positive value was added to observations of zero). Results are presented as odds ratios.

Poisson models were used for the three remaining metrics (Assessment pursuit rate, Pursuit rate and Total number of identifications). The raw counts from which 'Assessment pursuit rate' was calculated showed substantial overdispersion, but this was reduced markedly by including the appropriate time denominator as an offset, so the results are presented based on a Poisson rather than a negative binomial model. The model for 'Total number of identifications' included an adjustment for whether the case included a polyp or not, although the size of the prevalence effect was relatively unaffected by this adjustment.

Appendix B

Table: Estimated standard deviations (SD) of the case and reader random effect distributions

Metric	SD case	SD reader
Time to first pursuit	0.31	0.12
Total assessment time span	0.80	0.09
Assessment pursuit time	0.31	0.38
Assessment pursuit rate	0.13	0
Pursuit rate	0.15	0.20
Screen coverage		
Upper	0.42	0.58
Central	0.29	0.54
Lower	0.29	0.47
Total number of identifications	0.24	0.31
Any correct identification	3.03	0.28
Any incorrect identification	0.92	0.78
Videos with polyps	1.24	1.06
Videos without polyps	0.59	0.66

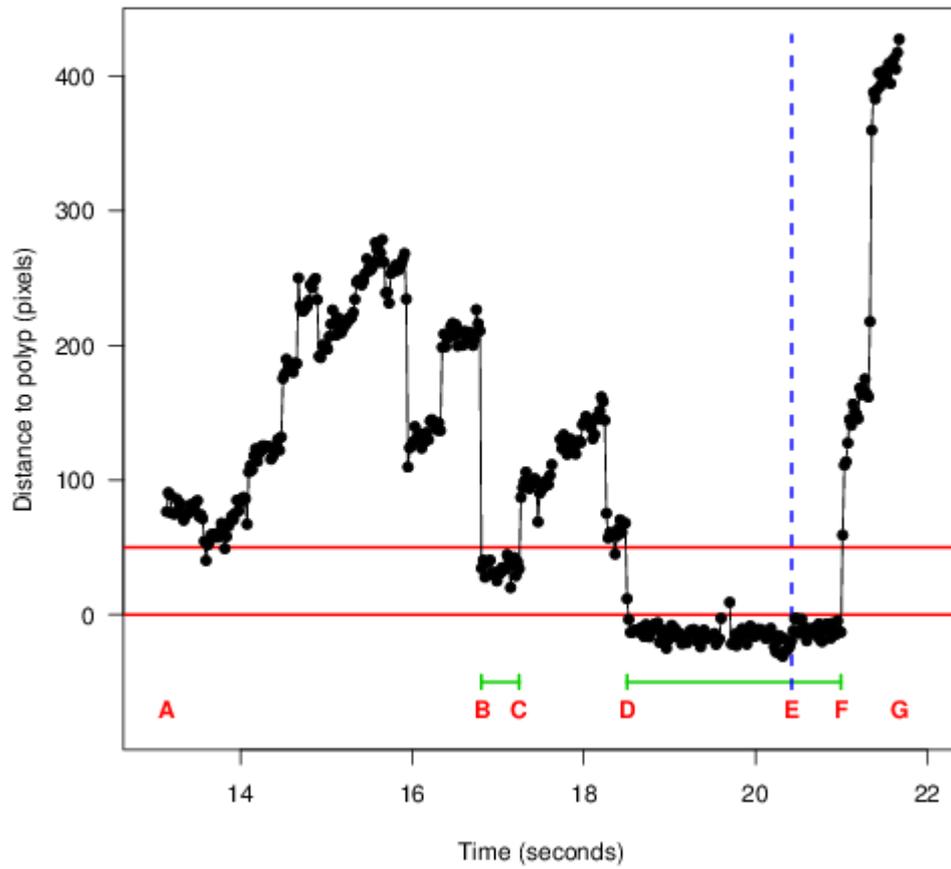


Figure 1

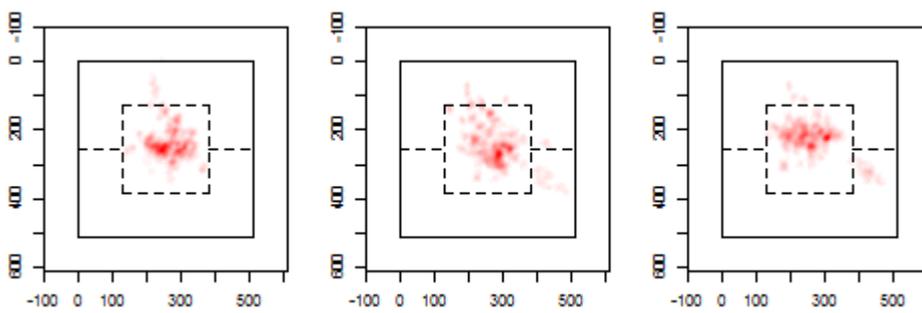
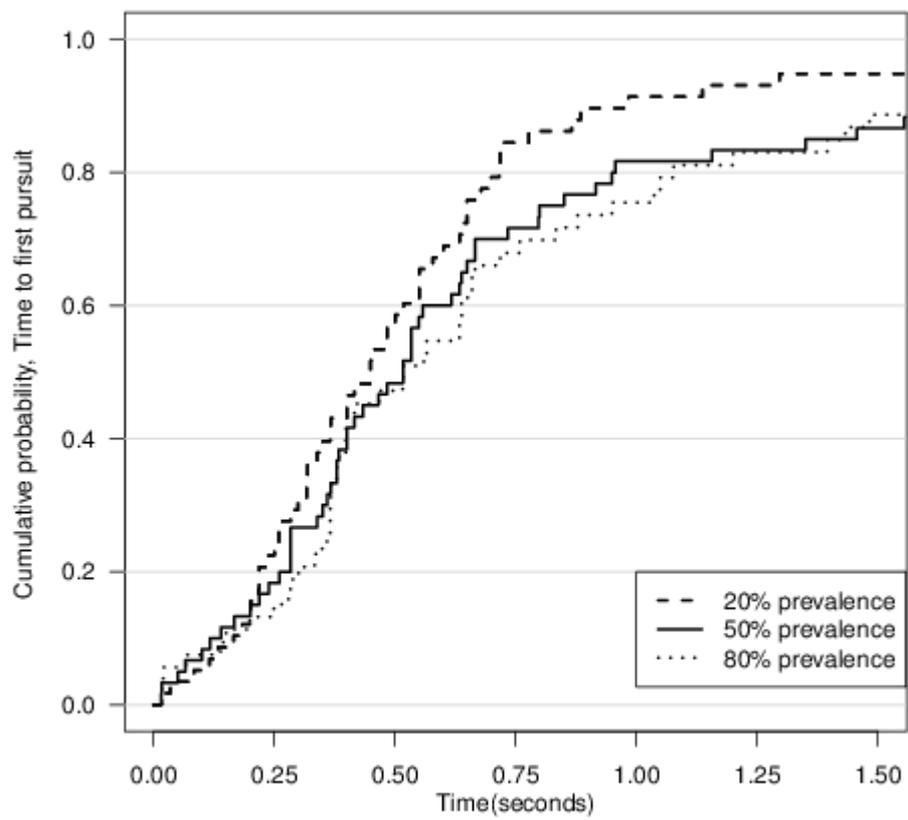


Figure 2



n at risk	0.00	0.25	0.50	0.75	1.00	1.25	1.50
20%	58	44	24	9	5	4	3
50%	60	49	31	17	11	10	8
80%	53	45	28	17	13	9	6

Figure 3

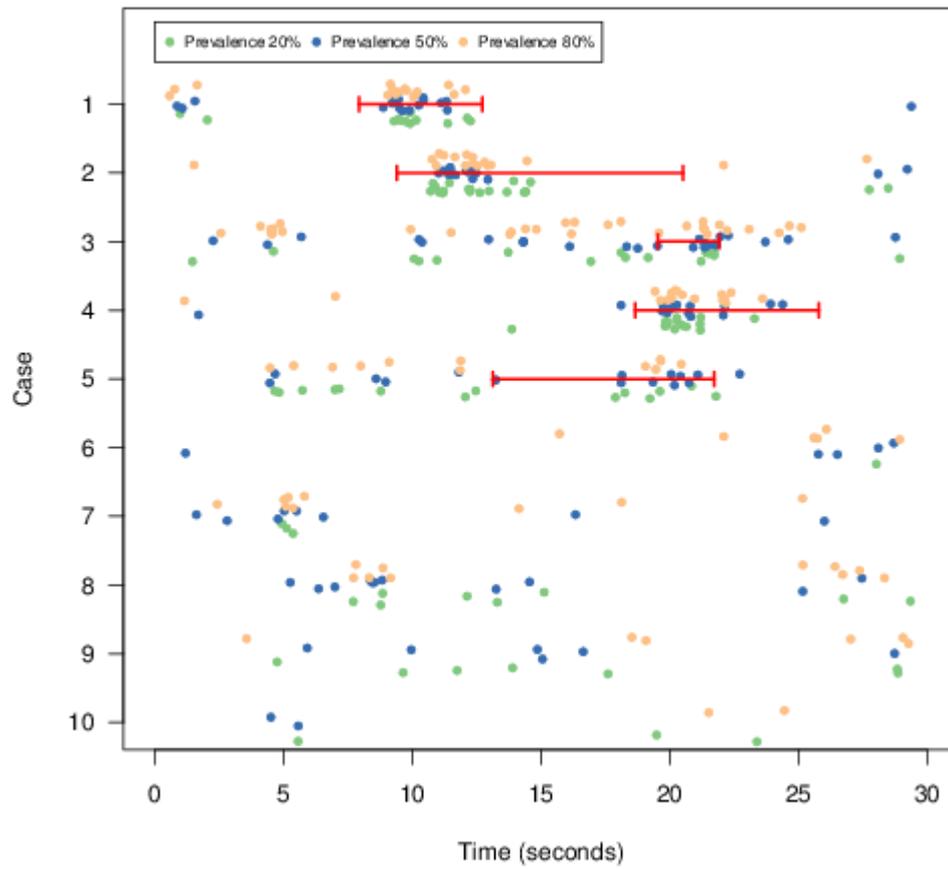


Figure 4

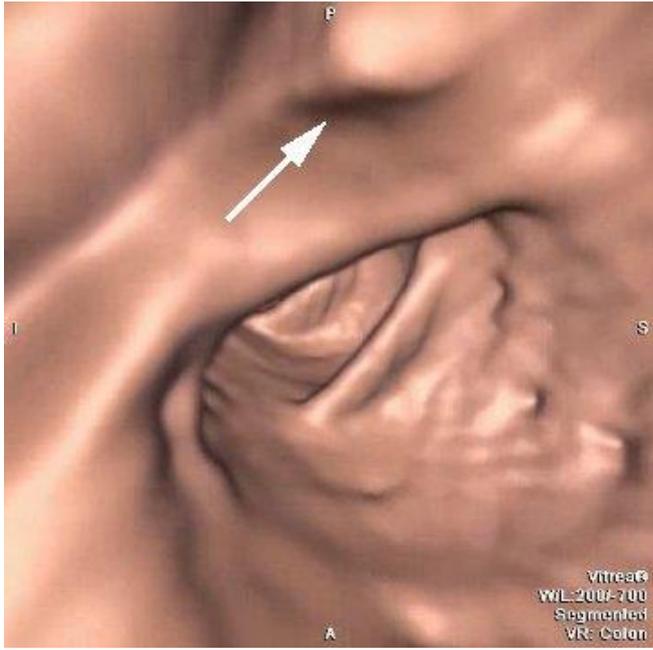


Figure 5