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The Gaze Relational Index as a Measure of Visual Expertise

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Abstract

Eye tracking is a powerful technique that helps reveal how people process visual information. This paper discusses a novel metric for indicating expertise in visual information processing, Named the *Gaze Relational Index* (GRI), this metric is defined as the ratio of mean fixation duration to fixation count. Data from two eye-tracking studies of professional vision and visual expertise in using 3D dynamic medical visualizations are presented as cases to illustrate the suitability and additional benefits of the GRI. Calculated values of the GRI were higher for novices than for experts, and higher in non-representative, semi-familiar / unfamiliar task conditions than in domain-representative familiar tasks. These differences in GRI suggest that, compared to novices, experts engaged in more knowledge-driven, top-down processing that was characterized by quick, exploratory visual search. We discuss future research aiming to replicate the GRI in professional domains with complex visual stimuli and to identify the moderating role of cognitive ability on GRI estimates.

Keywords

Visual expertise, information processing, eye tracking, fixations, professional vision

Introduction

Eye tracking is a powerful technique that helps reveal how people process visual information (Holmqvist & Andersson, 2017; Kok, 2019; Russo, 2019). Eye-tracking devices record the eye movements of people in the laboratory or in the field while they look at visual stimuli, such as photographs (Krupinski, 2019), source code (Hauser, Reuter, Hutzler, Mottok, & Gruber, 2018), video clips (Moore, Harris, Sharpe, Vine, & Wilson, 2019), animations (Lowe, Boucheix, & Menant, 2018), three-dimensional simulations (Gegenfurtner, Lehtinen, Jarodzka, & Säljö, 2017), and complex real-world scenes (Szulewski et al., 2019). Among the many parameters produced by eye tracking, a recorded fixation indicates where and how long somebody looks at a particular location in a display. By definition, fixations occur “when the eye remains still over a period of time" (Holmqvist & Andersson, 2017, p. 21). The number of fixations and their durations reflect how visual information is processed (Gegenfurtner, 2019; Hauser, Mottok, & Gruber, 2018; Holmqvist & Andersson, 2017; Russo, 2019).

The processing of information varies across individuals. In a study examining 60 French undergraduate domain novices who studied a piano mechanism from animations, Lowe and Boucheix (2016) found differences in the number and duration of fixations made as a function of the animation used and explained these in terms of depth of information processing. They noted that "longer fixation durations and lower fixation counts have been interpreted as indicating deeper processing which, in the context of the present study, are likely to reflect the intense, focused processing required to understand relationships. Conversely, shorter durations and higher counts likely reflect more exploratory, distributed processing (e.g., scanning and searching)" (Lowe & Boucheix, 2016, p. 80). Differences in relational versus exploratory processing were associated with mental model quality and overall performance in that study, with higher scores tending to occur when processing was more relational.

To analyze these differences in processing depth, Lowe and Boucheix (2016) converted the number and duration of fixations into a ratio which they termed the *relational index*: "The ratio of mean fixation duration (milliseconds) to fixation count was therefore used as a relational index to gauge the relative emphasis on relational versus exploratory processing" (p. 80). The gaze relational index is presented in the following formula:

$$\text{Gaze relational index (GRI)} = \frac{mean\ duration\ of\ fixations}{mean\ number\ of\ fixations}$$

The GRI is higher than 1 if the mean fixation duration in msec is larger than the mean number of fixations; in Lowe and Boucheix's (2016) study, these high GRIs were associated with relational processing. Conversely, the GRI is smaller than 1 if the mean number of fixations is larger than the mean fixation duration; in Lowe and Boucheix's (2016) study, this was associated with exploratory processing. If we assume that relational processing—with a tendency to fewer, but longer fixations—reflects the degree to which selected visual information is integrated with prior knowledge to build mental models and if we further assume that exploratory processing—with a tendency of more, but shorter fixations—reflects the degree to which visual information is explored and selectively attended to, then it would be interesting to examine how the GRI can be used as an indicator of visual expertise.

In recent decades, research on visual expertise has flourished (Boucheix, 2017; Donovan, Litchfield, & Crawford, 2017; Gegenfurtner & Van Merriënboer, 2017; Gruber, Jansen, Marienhagen, & Altenmüller, 2010) and produced a number of fascinating findings across a range of domains, including, but not limited to, sports (Hüttermann, Noël, & Memmert, 2018), medicine (Fox & Faulkner-Jones, 2017), and the arts (Francuz, Zaniewski, Augustynowicz, Kopiś, & Jankowski, 2018). Broadly defined, visual expertise reflects "maximal adaptations to the requirements of a vision-intensive task" (Gegenfurtner & Van Merriënboer, 2017, p. 2). For example, Williams and colleagues reviewed evidence how visual skills develop with expertise and how these skills are needed to anticipate and execute efficient movements in tennis and other sports (Williams, Fawver, & Hodges, 2017; Williams, Fawver, Broadbent, Murphy, & Ward, in press). In emergency medicine, Szulewski, Braund, Egan, Gegenfurtner, Hall, Howes, Dagnone, and Van Merriënboer (2019) reported that residents who performed better in a resuscitation simulation test were able to discriminate between task-relevant and task-irrelevant information and ignore distractors more often than the low performers. In these and many more documented instances of visual expertise, experts or high performers seem to allocate their attentional resources more effectively to task-relevant features of a visual scene and perceptually ignore task-irrelevant features. At the same time, experts are typically quicker and detect task-relevant information earlier than non-experts (Donovan et al., 2017; Gruber et al., 2010; Sheridan & Reingold, 2017a). Nevertheless, it is important to note that in order to capture the essence of expert performance, expertise research needs to employ task conditions that are as realistic, complex, and representative as possible (Ericsson, 2018; Feltovich, Prietula, & Ericsson, 2018; Norman et al., 2018; Williams et al., 2017). This allows experts to act in naturalistic laboratory settings or show their superior performance in the field. Often, this means using visualizations that are dynamic, with transient and multi-dimensional information, so that research participants are required to connect and representationally hold information from different areas and points in time, and engage in what Lowe and Boucheix (2016, p. 81) described as “hierarchical part-whole interlinking” when learning from animations. When these conditions prevail, it may be that GRI scores will reflect expertise-related differences in visual processing.

The purpose of the present paper is to explore the gaze relational index as a possible indicator of visual expertise. To this end, data from two published eye-tracking studies (Gegenfurtner et al., 2017; Gegenfurtner & Seppänen, 2013) that used 3D dynamic medical visualizations were re-analyzed. The aim was to determine if expertise differences in terms of the number and duration of fixations, which were documented in these studies, would be reflected in the GRI as well. If this was the case, a related aim of the study was to suggest use of the GRI as a novel indicator to the expertise research community.

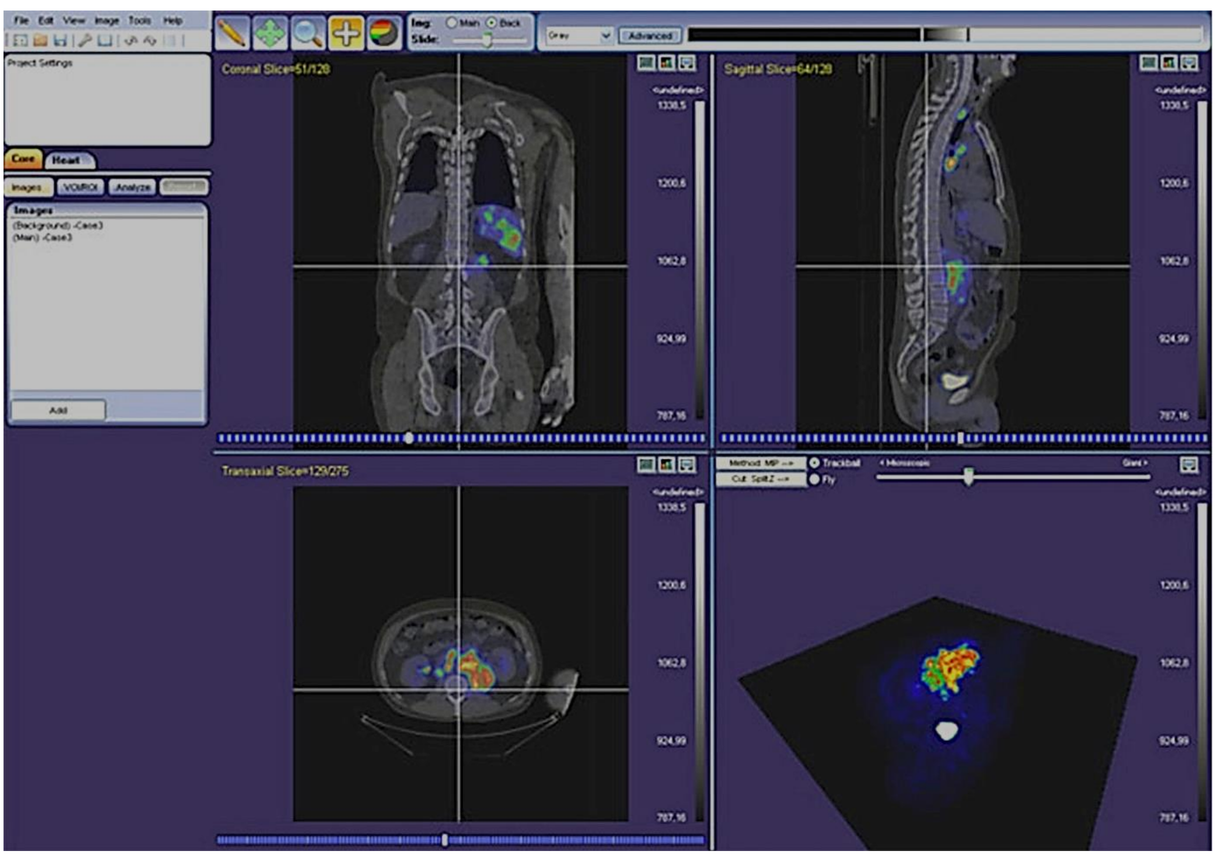

Figure 1. Example screenshot of the PET/CT visualization.

Study 1

The two studies shared a similar setting: diagnostic radiology and nuclear medicine. A prime interest was to understand visual expertise in interpreting dynamic, three-dimensional representations of the human anatomy and its functions. Study 1 (Gegenfurtner et al., 2017) compared eye movements by medical experts and novices in interpreting PET/CT visualizations. PET/CT is a newly introduced imaging technology that combines computer tomography (CT) and positron emission tomography (PET) to create a new kind of composite picture – a PET/CT visualization. CT is typically used in radiology to visualize human anatomy. In contrast, PET is typically used in nuclear medicine with the tracer fluorodeoxyglucose to visualize metabolism and the functional processes of the body. Figure 1 shows an example visualization. Participants in Study 1 were 23 individuals at two levels of expertise, 14 novices (medical students) and 9 experts (physicians), who were given the task of diagnosing one patient case. This case contained 550 static, two-dimensional, whole-body scans of a real patient (275 PET scans and 275 CT scans) that together formed one dynamic, three-dimensional PET/CT visualization, as shown in Figure 1, sized 1920 x 1200 pxl, on a 24" TFT monitor. The participants' task was to produce a diagnosis from the presented patient case; this task corresponds with a problem-solving task, the highest level in Gegenfurtner, Lehtinen, and Säljö's (2011) four-level model of task complexity in the comprehension of visualizations.

Eye movements were recorded with a Tobii T60XL remote eye tracker with a temporal resolution of 60 Hz. The PET/CT visualizations were dynamic: Participants could zoom in and out, and interrogate different planes, similar to what is possible with digital maps. Because the stimulus was dynamic and controlled by the user, areas of interest were transient and varied in size. An area of interest was defined as any part of the visual stimulus that contained diagnostically relevant (that is: task-relevant) information. Fixations outside these areas of interest were defined as fixations on task-irrelevant information. The eye movement recordings were segmented, "with the length of each segment determined by the maximum amount of time during which AOIs were visible within each segment" (Gegenfurtner et al., 2017, p. 215). The number and duration of fixations were averaged across participants.

These analyses resulted in a mean number and duration of fixations in msec for novices and experts on task-relevant and task-irrelevant information. Tables 1 and 2 present these estimates, together with the new GRI as an indicator of visual expertise. For experts, the GRI was 0.76 on task-relevant versus 0.42 on task-irrelevant areas. For novices, the GRI was 0.78 on task-relevant versus 0.43 on task-irrelevant areas. These findings suggest that the GRI was marginally higher for novices than for experts, and higher when processing task-relevant compared with task-irrelevant information.

Table 1. Gaze Relational Index (GRI) by Levels of Expertise for Task-Relevant Information

	Fixation Number			Fixation Duration			GRI
	M	*SE*	*95% CI*	*M*	*SE*	*95% CI*	
Experts	253.22	42.06	156.22; 350.22	191.85	27.12	129.31; 254.39	0.76
Novices	232.71	25.92	176.70; 288.72	181.90	45.65	82.28; 280.52	0.78

Table 2. Gaze Relational Index (GRI) by Levels of Expertise for Task-Irrelevant Information

	Fixation Number			Fixation Duration			GRI
	M	*SE*	*95% CI*	*M*	*SE*	*95% CI*	
Experts	87.00	18.75	43.77; 130.23	36.44	10.75	11.64; 61.24	0.42
Novices	127.93	25.86	72.06; 183.80	55.50	13.35	26.66; 84.34	0.43

Study 2

Study 2 paralleled Study 1 in that it also examined the eye movements while interpreting dynamic, three-dimensional medical visualizations. In Study 2 (Gegenfurtner & Seppänen, 2013), nine experts—four radiologists and five nuclear medicine physicians—had the task of diagnosing a patient case in a familiar, semi-familiar, and unfamiliar task condition. In the familiar condition, participants with a background in PET diagnosed the patient case displayed in PET, while participants with a background in CT diagnosed the patient case displayed in CT. In the unfamiliar condition, participants with a background in PET diagnosed the patient case displayed in CT, while participants with a background in CT diagnosed the patient case displayed in PET. In the semi-familiar condition, the patient case was displayed in PET/CT, as shown in Figure 1. To minimize any order effects, task presentation order was randomized. Materials, tasks, measures, and analyses paralleled those in Study 1.

Tables 3 and 4 present the mean number and duration of fixations together with the GRI in the three task conditions. In the familiar task, the GRI was 0.54 on task-relevant and 0.43 on task-irrelevant areas. In the semi-familiar task, the GRI was 0.74 on task-relevant and 0.50 on task-irrelevant areas. In the unfamiliar task, the GRI was 0.66 on task-relevant and 0.48 on task-irrelevant areas. These results show that the GRI was higher in the semi-familiar and unfamiliar task conditions compared with the familiar condition, and higher when processing task-relevant compared with task-irrelevant information.

Table 3. Gaze Relational Index (GRI) by Condition for Task-Relevant Information

	Fixation Number			Fixation Duration			GRI
	M	*SE*	*95% CI*	*M*	*SE*	*95% CI*	
Familiar	446.78	68.06	289.84; 603.72	240.09	34.03	161.62; 318.56	0.54
Semi-Familiar	511.11	82.16	321.64; 700.58	378.38	56.80	247.41; 509.35	0.74
Unfamiliar	692.89	106.62	447.02; 938.76	458.30	65.24	307.86; 608.74	0.66

Table 4. Gaze Relational Index (GRI) by Condition for Task-Irrelevant Information

	Fixation Number			Fixation Duration			GRI
	M	*SE*	*95% CI*	*M*	*SE*	*95% CI*	
Familiar	159.11	21.67	109.15; 209.07	68.85	9.05	47.98; 89.72	0.43
Semi-Familiar	149.00	24.98	91.40; 206.60	71.50	15.95	34.72; 108.28	0.50
Unfamiliar	187.11	22.59	135.01; 239.21	89.72	12.40	61.13; 118.31	0.48

General Discussion

This paper explored the potential utility of GRI as an indicator of visual expertise. By re-analyzing data from two studies, the calculated GRI values were marginally higher for novices than for experts, and higher in semi-familiar/unfamiliar task conditions than in the familiar task, reflecting a more exploratory processing approach (Lowe & Boucheix, 2016). Although statistically non-significant, the finding is consistent with visual expertise being associated with less bottom-up processing of visual information and more knowledge-driven top-down influences that help the expert quickly scan the visual field and selectively attend to relevant features in domain-representative tasks. From a theoretical perspective, this result is in line with long-term working memory theory (Ericsson, 2017): Expertise increases the speed of information processing owing to retrieval structures, which bridge working memory and long-term memory (Delaney, 2018; Ericsson, 2017). Extensive knowledge in long-term memory therefore reduces the time needed for mental model construction in working memory and guides attentional resources to task-relevant elements of the visualization. This advantage of expertise, reflected in visual search patterns visible in the GRI, is documented in a number of studies in the field of expertise research (Gegenfurtner, 2019; Gruber & Harteis, 2018; Patel, Kaufmann, & Kannampallil, in press; Sheridan & Reingold, 2017b; White et al., 2018).

It is legitimate to ask why this new indicator is needed. What additional benefits might be offered by the GRI? One could argue that the same information that is captured by the GRI is also available through inspecting the number and duration of fixations. This is certainly true because the GRI uses the ratio of both measures. However, the GRI *integrates* these two estimates. On one hand, this integrated metric affords a quicker interpretation of information processing differences, and on the other, it offers an opportunity for a combined analysis that is unavailable if fixation number and duration are analyzed separately. We should note that the size of the GRI will differ by scale, so we propose to report fixation duration in msec for reasons of standardization and comparability. Further, a third benefit of the GRI relates to the convincing argument of Gobet (2018) that the future of expertise research lies in cross-disciplinary work to study the transversal themes of “definition/identification of expertise” and “search” (Gobet, 2018, p. 102). The GRI is the result of such boundary crossing between the research arenas of visual expertise and animation-based learning because the relational index as a metric for processing depth when learning from animations was re-contextualized as a metric for processing efficiency when inspecting visual material (Boucheix & Lowe, 2017; Lowe & Ploetzner, 2017).

Despite the GRI having potential as a novel metric for indicating expertise, more research is needed for replication and to test the GRI’s usefulness in other domains and types of visual representations. It can be argued that because the GRI captures explorative versus relational processing, the index might be especially suitable for use with dynamic and multi-dimensional visualizations under conditions of information transience (Fichtel et al., 2019; Kok et al., 2018; Seppänen & Gegenfurtner, 2012; Szulewski et al., 2018) or ideally outside lab settings in the field, with mobile eye trackers, mirroring the full complexity of visual input that experts routinely deal with in their everyday work surroundings (Billett, Harteis, & Gruber, 2018; Lehtinen, Gegenfurtner, Helle, & Säljö, in press). Another direction for future research relates to the role of general cognitive abilities and their potential influence on the GRI (Hambrick, Burgoyne, & Oswald, in press) because it can be assumed that working memory capacity and visual-spatial ability might moderate fixation data produced by eye-tracking technology. This is arguably a limitation that does not only hold for the GRI but for eye-tracking research at large.

In conclusion, this paper examined the potential utility of the gaze relational index as a marker of processing depth and, ultimately, visual expertise. Based on the innovative conceptualization of Lowe and Boucheix (2016) and the re-analysis of two eye-tracking data sets, the likely usefulness of the GRI as a combined measure of fixation duration and count to trace visual expertise was explored. Future research is warranted to extend the first steps presented here to the examination of experts', intermediates', and novices' eye movements while interpreting complex visual scenes.

Author's Declarations

The authors declare that there are no personal or financial conflicts of interest regarding the research in this article.

The authors declare that they conducted the research reported in this article in accordance with the Ethical Principles of the Journal of Expertise.

The authors declare that they are not able to make the dataset publicly available but are able to provide it upon request.

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