Differences between Professionals and Students in Their Visual Attention on Multiple Representation Types While Solving an Open-Ended Engineering Design Problem

Ananna Ahmed[1]; David Hurwitz, A.M.ASCE[2]; Sean Gestson[3]; and Shane Brown, F.ASCE[4]

Abstract: Students and professionals from a variety of domains have demonstrated different approaches to problem solving. These two populations have displayed differences when using and perceiving multiple representations of problem-solving tools. In the domain of transportation engineering, this difference has yet to be evaluated in detail. This study addresses that knowledge gap. We used a mixed-methods approach with measurements of eye movements for visual attention and reflective interviews to gather participants' reported representation use and problem-solving assumptions with three taxonomies of representations (equations, graphs, and flowchart) because they solved an open-ended design problem. Visual attention (VA) was recorded with a head-mounted eye-tracking device. Reflective interviews were used as a self-reported depiction of overt VA on the selected representation, and to record assumptions made by each participant to solve the problem. Equations, graphs, and flowcharts received different magnitudes of statistically significant VA for both groups. Professionals had a significant difference in VA between the flowchart/equation and graph representations, whereas students showed a difference in all three categories. Professionals generally chose representations with higher complexity (use of different combinations of representations) than students, as reflected by their frequency of conjoining representation choices and their associated assumptions. Professionals commonly approached problem solving by documenting specific assumptions, whereas students approached the problem more generically. Efficient information extraction occurred for professionals, but it took more time for them to solve the problem than novices. Novices frequently utilized the flowchart. Differences in performance may be explained by professionals using conceptual frameworks, or rules for interpreting and navigating the problems that were potentially developed through exposure to the domain of knowledge and deep understanding of the subject matter. **DOI: 10.1061/(ASCE)EI.2643-9115.0000044.**

Introduction

Engineering education development is fundamentally aimed at helping the student develop robust problem-solving skills in various content spaces, in addition to helping them learn foundational knowledge. Engineering practice and education have a bilinear relationship (Cheville 2014). Industry frequently adopts new approaches, ideas, and technology, which are then incorporated into the engineering curriculum. Education philosophers and scientists thrive to achieve as pragmatic a depiction of engineering problems in a classroom setting as is feasible, considering the gap between education and in-field demands (Korte et al. 2015). Policy and curriculum are developed and updated based on the changing needs of industry challenges (Earnest 2006).

There is a substantial need to understand this interaction between industry and education, which manifests itself through research on experts, frequently used interchangeably as, engineering professionals versus novices, engineering students (Bruder and Hasse 2019; Morphew et al. 2015). (Although some disciplines consider young professionals as novices.) Practicing engineers need to gain competence in using varied concepts and applications to solve problems, but engineering students are exposed to isolated segments of a preformulated problem for the benefit of simplified learning (Ali 2015). Until recently, conventional teaching methods have relied heavily on theoretical ideas, whereas young professionals need to identify problems in an unguided, complex environment (Jonassen et al. 2006). Professionals are enculturated to domain-specific problem-solving approaches. Previous experience influences how one approaches a new problem (Korte et al. 2015). Students become accustomed to solving segmented problems; as such, their strategy and approach differ from those of professionals. Thus, it is important that young professionals develop approaches they can apply to unstructured, real-world problems, justifying their decisions along the way (Cristino 2011). It is important to understand the differences between engineering professionals and students in their application of approaches and strategies to open-ended problems (Brown et al. 2019).

Visual attention (VA) has been compared with a dark room with a single spotlight to guide foveated attention (Shulman et al. 1979). Gaze patterns across information visually provide a detailed impression of the distribution of attention. Studying eye movement, therefore, provides an idea of how VA prioritizes and selects what cognition chooses as important over large amounts of sensory

[1]Graduate Research Assistant, School of Civil and Construction Engineering, Oregon State Univ., 101 Kearney Hall, Corvallis, OR 97333. Email: ahmedana@oregonstate.edu

[2]Associate Professor, School of Civil and Construction Engineering, Oregon State Univ., 101 Kearney Hall, Corvallis, OR 97333 (corresponding author). ORCID: https://orcid.org/0000-0001-8450-6516. Email: david.hurwitz@oregonstate.edu

[3]Graduate Research Assistant, School of Civil and Construction Engineering, Oregon State Univ., 101 Kearney Hall, Corvallis, OR 97333. ORCID: https://orcid.org/0000-0002-4796-1410. Email: gestsons@oregonstate.edu

[4]Professor, School of Civil and Construction Engineering, Oregon State Univ., 101 Kearney Hall, Corvallis, OR 97333. ORCID: https://orcid.org/0000-0003-3669-8407. Email: Shane.Brown@oregonstate.edu

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information at any given time. This phenomenon of depicting the most recent interest is known as selective attention (Frintrop et al. 2010). Studies have reported differences in VA assigned to areas of interest (AOIs) between experts and novices. In this paper, we use VA to refer to a visually guided cognitive ability to select stimuli and respond to the stimuli as per a person's associated memory that is behaviorally relevant in a circumstance (Corbetta and Shulman 2002). In other words, VA is a physiological manifestation of attention at a given time. By contrast, the conscious assignment of cognitive attention is an act that a participant thinks they have deliberately attended to. Thus, the question of using VA as a cursor for the assignment of cognitive attention should be investigated further. In parallel, how cognitive attention and VA, with or without being wholly representative of each other, vary for expert and novice participants also needs exploration. This question may provide insight into how these groups engage their cognition to attain completion of the same task (Rayner 1977).

We investigated VA to determine differences in where professionals versus students assign their attention.

Literature Review

The following literature review explores how professionals and students act differently in assigning cognitive processes and VA. Relationships of VA and problem-solving strategies are explored. Tools and methods to establish a relationship between VA and cognitive attention assignment are also described.

Use of Multiple Representations

Concepts can be formulated using various representations. Most disciplines use multiple representations, including textual, diagrammatic, and formulaic representations, to scaffold a wide spectrum of learning environments (Van Someren et al. 1998). Properties or features of different representations share the common goal of transferring a deep understanding of subject matter (Van Labeke and Ainsworth 2001). Multiple representations can be complimentary, fulfilling different elements of the concept. According to Ainsworth (1999), multiple representations can provide computational efficiency or a better understanding of the subject matter. Why different factors are added to the representations and what role those factors play in real-life problem solving are fundamental to this understanding. The type of information or problem provided can guide which representation a problem solver selects. In certain cases, multiple representations can be a means to reach the same conclusion by considering different aspects of the problem (Abadi et al. 2019). In practice-based industries, such as transportation engineering, representations have evolved together with the evolution of the philosophy and technology of engineering practices. Industry prefers to adopt and develop practice-ready representations rather than theoretical ones (Turochy et al. 2013). Disciplines like multimedia design, aircraft operation, and laparoscopic surgery have studied these differences, whereas such studies are lacking in the engineering domain.

Information delivery theory postulates that problem solvers with prior knowledge or familiarity with similar problems or representations tend to be more efficient in receiving information (Hagerty et al. 2002). A learning environment with multiple alternative problem-solving methods (e.g., formulaic, pictorial, textual) requires the engagement of higher-level cognitive processes: specifically, a mental mapping to connect the dots by understanding the underlying structure, dictated by previous experience (Kokotovich 2008). However, instructional design with multiple representations has the risk of being poorly designed. The *split attention effect* of learning suggests that if different modalities of information transfer are being used, learners' cognitive attention can be divided between representations (Chandler and Sweller 1992). This effect is minimized when less attention is allocated on individual representations and more attention is focused on solving the problem while extracting the minimum required information (Gog et al. 2005). Hence, the efficient use of multiple representations requires cohesive integration of different modes and conceptual framework. The conceptual framework provides an overall picture of the problem in a specific domain that includes relevant variability and context. However, more work is needed to understand the perception and utilization of information by experts versus novices.

Professionals (Experts) versus Students (Novices)

Differences in Problem-Solving Strategies and Processes

Novice participants, when faced with multiple contextual representations, struggle due to lack of experience, and lack of strategies to efficiently use the multiplicity offered them (Hagerty et al. 2002). Learners or novice professionals tend to focus on one representation or a subset rather than using a combination of representations (Schwonke et al. 2009). From the perspective of cognitive science, informationally equivalent representations are not necessarily computationally equivalent (Breslow et al. 2009). Therefore, developing efficient strategies for the use of multiple representations appears to be an acquired skill. Studies of problem-solving strategies and associated cognitive engagement remain of interest not only for assessment purposes but also for training novice professionals to attain increased proficiency in problem-solving. Therefore, the question of how engineering professionals and students are using a multiplicity of representations should be studied further.

Factors like familiarity, previous exposure, effects of learning and situated cognition, and long-term memory help form a professional's problem-solving strategy (Gegenfurtner et al. 2011). For visual tool-based problem-solving strategies, where one or more tools to solve the problem are represented visually explaining the relationships between factors, the attention-sharing model seems to explain memory association in a defined manner. According to this model, several studies have found that experts prioritize accuracy by allocating VA to what is important and relevant (Gegenfurtner et al. 2011). Experts seem to have a lower number of fixations but relatively higher average fixation durations than novice participants (Kasarskis et al. 2001). Differences in cognitive processes between expert and novice participants seem to be based on the ability to receive information in different ways. Professionals, therefore, seem to focus their attention on what they deem is important in extracting information and strategizing problem-solving. Understanding what professionals consider to be important to look at and how their perceptions differ from those of engineering students can contribute to the body of knowledge on engineering education.

Information and Pattern Extraction Efficiency

Finding meaningful patterns in a stream of information is a foundation of problem-solving in the cognitive realm. Experts, based on experience in their discipline, can find meaningful patterns and extract meaningful information faster than novices (Wolff et al. 2016). Experts reach a final decision faster and with greater accuracy (Tsui 2003). Professional experience has a positive influence on decision making by helping to distinguish relevant from irrelevant information (Meeuwen et al. 2014). Novice participants were found to explore all presented alternatives with their visual search to compensate for their gaps in experience and associated cognitive development (Boshuizen and Schmidt 2008).

Gaze Pattern When Approaching a Task

Previous studies found meaningful differences in gaze patterns between expert and novice professionals. In general, experts had focused VA, whereas novice attention was comparatively dispersed. Wolff et al. (2016) studied expert and novice teachers in a disruptive classroom setting. Experts seemed to maintain VA in an objective-task-oriented manner based on what was deemed important, whereas the VA of novices was scattered around the classroom. Researchers concluded that expert viewing was founded on previously gained knowledge, whereas novice attention was image-driven. Expert teachers, in this experiment, attended to the problem in detail, whereas novice teachers skipped parts of it. Studying gaze pattern differences could involve observing VA parameters, such as the number of fixation points on representations and average and total fixation durations, and using that data to categorize experts versus novices. As experts and novices may display differences in VA attributes, cluster analysis or Kernel density analysis may be useful in classifying those differences.

Eye Tracking to Study Attention

Eye tracking has been implemented to understand meaningful gaze behavior since the 1950s when static cameras were used to study the gaze behavior of pilots (Fitts et al. 1950). Different techniques and parameters, such as pupil position, fixation frequency, and duration, dwell time, and saccadic inference, have been developed (Tien et al. 2014). In addition to representing behavioral markers, these parameters are used to represent the ability to complete certain tasks. Sport, culinary, medical, aviation, and construction fields have found eye tracking to be predictive of problem-solving ability (Gegenfurtner et al. 2011). Attempts have been made to differentiate expert and novice skills based on eye tracking in different fields.

More specifically, the use of eye tracking to understand the spatial and temporal properties of VA distributed in a finite space gained popularity since the late 1990s (Rayner 1998). Spatial parameters, including fixation location and saccadic trails, were found to be important in interface-based learning media. Temporal parameters include total and average fixation duration and fixation count, provide information about overt VA (Salvucci and Goldberg 2000). However, VA data alone cannot elucidate why temporal attention is focused on an AOI (Schwonke et al. 2009). In addition, looking at something does not necessarily mean cognitively attending to that thing. Thus, VA data could be skewed when considering covert attention (Snowden et al. 2012). We addressed this gap is by adding reflective interviews to the methodology where we specifically asked questions about what representation(s) participants used.

Beyond the realm of assessment, a recorded performance of experts and comparison with novice professionals can be used for focused training (Vine et al. 2012). Virtual training platforms can also benefit from such initiatives. However, eye tracking alone only provides information on where a professional is looking (Tien et al. 2014). To develop a reproducible framework, a reflective verbal representation technique with eye tracking can provide information on preferential gaze behavior coupled with cognition (Galesic et al. 2008).

Reflective Interview

Methods that extract information on what the person is thinking during eye tracking can provide insight into underlying cognitive processes (Abadi et al. 2019). Such methods include the thinking aloud strategy, clinical or cognitive interview, reflective interview, and others (Guan et al. 2006). Information-affirming observations of eye tracking are also important to validate such methodologies. Reflective interviews are instrumental in qualitative analyses in behavioral science applications (Sofaer 2002). They provide a platform to document decisions, choices, and cognitive processes and responses while solving a problem (Sudman and Bradburn 2003).

Professionals and students differ in how they approach problems and strategize to solve problems, maximize problem-solving tools and modes, and extract meaningful patterns and information. Several applied knowledge fields have successfully studied these aspects through VA to determine assigned attention and correlate assigned attention to cognitive processes. Examples of the value of studying expert versus novice performance in training and curriculum design are substantial (Earnest 2006; Gog et al. 2005; Wolff et al. 2016), but transportation engineering lacks such a body of knowledge.

The goal of this study is to understand more about minimizing the gap between industry demands and preparing students for the pragmatic technical demands of transportation engineering. This study implemented eye tracking coupled with a reflective interview to identify the selected representation and assumptions made to solve the problem, to address the following research objectives:

1. How does the allocation of VA across multiple representations relate to the representation used by participants?
2. How does the allocation of cognitive attention (reflected in VA) differ as professionals and students' approach, strategize, and solve a problem?
3. How do professionals and students differ in their allocation of VA on multiple representations?

Methodology

The methodological approach employed in this study was adopted from previous work (Abadi et al. 2019). Engineering students and engineering professionals participated in this study and solved a transportation engineering design problem. Data collection was designed to gather VA data from an eye-tracking system and a walkthrough of the problem-solving process from a reflective interview. Data were analyzed qualitatively using visualization and statistical trend analysis and quantitatively using statistical methods.

Design Problem Outline

Engineering professionals and students were provided with the same problem statement and representations to assist in solving the problem. Participants were asked to recommend the most appropriate left-turn treatment (protected, permitted, protected-permitted, or split phase) on each approach of a four-legged intersection with two lanes on each approach. Participants were provided peak hour traffic volumes per movement (right, through, and left), speed limit, sight distance, and the number of left-turn-related crashes on each approach. Participants were encouraged to make assumptions or alter the geometric design as needed. During reflective interviews, such assumptions and modifications were investigated, and a solution walkthrough was prompted.

Representations

Three representations were provided to facilitate the problem solution. Representations were chosen from a pool of widely used representations in teaching and industry settings. All representations were empirical and included multiple fundamental ideas to consider for left-turning signal treatment. The representations were specifically chosen for the spread of their scope and predominance in textbooks and traffic manuals (i.e., overall in the industry). Representations were classified as: formulaic (set of equations), graphical (graph), and tabular (flowchart). Each representation individually provides information that can lead to the same solution for the problem but employs slightly different fundamental ideas and boundary conditions. For example, the formulaic representation was a set of equations sourced from Roess et al. (2011) that is based on vehicular volumes (left-turn and opposing through movement). This representation results in a binary answer to whether some protection should be considered. The graph was sourced from the NCHRP Signal Timing Manual, 2nd edition, and includes opposing speed with left-turning volume to make a binary recommendation about protection. The flowchart, sourced from the NCHRP Signal Timing Manual, 2nd edition (Lozner et al. 2015), includes several factors like the number of crashes, sight distances, traffic volumes, and speed limits, and recommends either protection, protected-permissive, or permissive left-turn phasing.

Participants

Professional participants were recruited from two public transportation engineering agencies and two private consulting firms by contacting the corresponding managers. Professionals totaled 23 participants with 2–17 years of experience in the transportation industry with a certification of field practice. Professionals reported experience in signal timing, urban planning, and traffic design. Every participant in this group had successfully completed the fundamentals of engineering exam. This was used as selection criteria, but specific years of experience were not recorded. Summary of familiarity to these representations, specific experience in working with these representations, and experience in the field or a closely related field were recorded in Table 1. One out of 23 participants had seen these representations or parts before and two had only seen state-mandated version of these representations. Ten participants had experience engaging with these representations, four had used similar department of transportation guidelines. Eight participants did not work with these representations but were exposed through handbooks and training in their agency. Participants represented both private and public industry, and approximately 40% were female. Engineering students were recruited from the Oregon State University School of Civil and Construction Engineering through flyers and email promotions. Students had taken the Introduction to Highway Engineering undergraduate-level course, a required three-credit, quarter-long class typically taken in the junior year, and none of them had taken any advanced transportation engineering courses until then. A total of 14 student participants were included. In total, the 37 participants produced more than 15,000 fixation points in eye-tracking analyses. For desirable statistical significance, eye-tracking studies with 15–20 samples are considered acceptable and frequently used across different disciplines (Eye Tracking Incorporation 2013).

Data Collection

The involvement of human subjects required Institutional Review Board (IRB) approval. The protocol was approved at Oregon State University (study no. 6959). The study was divided into two components: eye-tracking and reflective interviews. The experimental setup was uniform for all participants, and only one participant solved the problem at a time. Eye-tracking data were collected while participants solved the problem, which was presented on a 24-in. computer monitor in a single PowerPoint slide. The slide had five components (problem statement, definition, equation, graph, and flowchart) separated by borderlines considered as the AOIs.

Table 1. Summary of exposure and domain knowledge of professional participants

Professional participants	Are you familiar with these representations?	Used these specific representations?	Do you work in this domain?
1	Yes	No	Yes
2	Yes	Yes	Yes
3	Yes	Yes	Yes
4	Yes	Yes	Yes
5	No	DOT guidelines	Yes
6	Yes	Yes	Yes
7	Yes	Yes	Yes
8	Yes	Yes	Yes
9	Yes	Yes	Yes
10	Yes	Yes	Yes
11	Yes	DOT guidelines	Yes
12	Yes	Yes	Yes
13	Yes	State guidelines	Yes
14	Yes	State guidelines	Yes
15	Yes	Yes	Yes
16	Yes	No	Yes
17	Yes	Yes	Yes
18	State guideline	No	Yes
19	Yes	No	Yes
20	Yes	No	Yes
21	Yes	No	Yes
22	State guideline	State guidelines	Yes
23	Yes	DOT guidelines	Yes

The top left corner was occupied by the problem statement, given information, and a schematic of the intersection in plan view. The rest of the area was occupied by three representations and a list of definitions. Pen and paper were provided to participants to prepare their responses. The problem layout is presented in Figs. 1–5. At the beginning of the experiment, participants were briefed about the problem and steps of the experiment. Upon their consent, the eye tracking device was set up. A timer was used to record completion time. After self-reported completion of the problem, researchers asked predesigned questions in the reflective interview.

Eye Tracking

Participants were instrumented with a mobile eye-tracking device (Mobile Eye-XG platform by Applied Science Laboratories, Bedford, Massachusetts), which records the pupil location and monitors fixation and gaze pattern information. Fixations were set at the threshold of 0.1 s of VA on any location. Among different fixation categories (silent reading, oral reading, scene perception, and visual search), the visual search was most appropriate for this study. The typical average fixation duration lies between 0.18 and 0.275 s (Rayner and Castelhano 2007). Therefore, 0.1 s is an acceptable threshold. This aspect of the experiment was designed to obtain VA information while participants solved the problem.

Reflective Interview

The second component of data collection involved a semistructured reflective interview. The following questions were asked to each participant: Were you familiar with the representations provided with the problem? Was simplicity a concern when approaching these representations? What assumptions did you make outside of the stated assumptions to solve this problem? Why did you make those assumptions? Walk us through the steps that you took to solve this problem. Elaborate on your reasoning behind each step. How did prior experience or intuition guide you through the solution

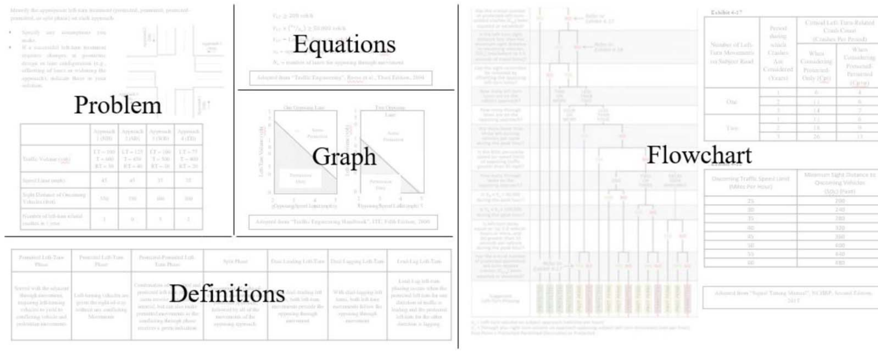
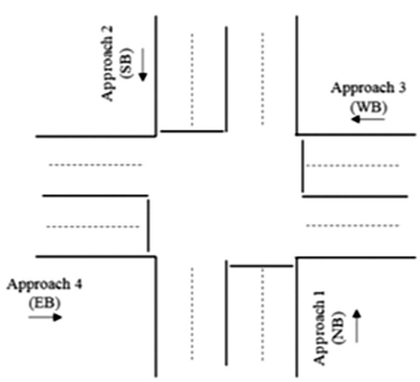


Fig. 1. Schematic problem layout as presented to the participant.

process? How confident are you with the answer you provided? Are there additional resources that you use or prefer to use to solve these problems? These questions were supplemented with additional probing questions based on the individual responses of the participants. An example of this would be asking the participant for more details about their choice of a representation or their reasoning for choosing one representation over another. For this study, we used participant responses to questions about what representation(s) participants used to solve the problem and what assumptions participants made while solving the problem. This study was part of a larger project that used all data collected in the reflective interviews to analyze and correlate time-stamped VA data to the problem-solving steps and rationales explained by the participant immediately after solving the problem. Results from qualitative analysis of the complete interview data are documented in a previous publication (Abadi et al. 2019).

Identify the appropriate left-turn treatment (protected, permitted, protected-permitted, or split phase) on each approach.

- Specify any assumptions you make.
- If a successful left-turn treatment requires changes in geometric design or lane configuration (e.g., offsetting of lanes or widening the approach), indicate these in your solution.



	Approach 1 (NB)	Approach 2 (SB)	Approach 3 (WB)	Approach 4 (EB)
Traffic Volume (vph)	LT = 100 T = 600 RT = 30	LT = 125 T = 450 RT = 40	LT = 100 T = 500 RT = 30	LT = 75 T = 400 RT = 20
Speed Limit (mph)	45	45	35	35
Sight Distance of Oncoming Vehicles (feet)	350	350	300	300
Number of left-turn related crashes in 1 year	3	0	3	2

Fig. 2. Left-turn treatment problem.

Data Reduction

Data reduction was performed in two steps. Eye-tracking data were recorded for every participant throughout their problem solving (~15 min per participant on average). Fixations of 0.1 s or more were recorded; therefore, a high volume of data was produced. These data were reduced using ETAnalysis version 3.8.2 software. For further analysis to define patterns and comparisons between professionals and students, MATLAB and SAS were used. Reflective interview data on representation choice and assumptions made during the problem solving was coded using Dedoose, a qualitative data analysis software.

Data Analysis

Analytical and quantitative data analysis techniques were used to answer three research questions.

Analytical Techniques

Eye-tracking data were visualized together with choices and/or rationales, and trends were analyzed to investigate analytical aspects of the first research question (*How does the allocation of VA across*

$V_{LT} \geq 200$ veh/h

$V_{LT} \times (v_o/N_o) \geq 50{,}000$ veh/h

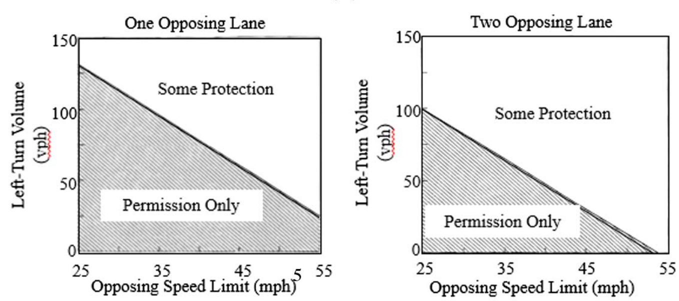
V_{LT} = Left-turn flow rate, veh/h

v_o = opposing through movement flow rate, veh/h

N_o = number of lanes for opposing through movement

Adopted from "Traffic Engineering", Roess et al., Third Edition, 2004

(a)



Adopted from "Traffic Engineering Handbook", ITE, Fifth Edition, 2000

(b)

Fig. 3. (a) Equations (data from Roess et al. 2011); and (b) graphs (data from ITE 2000).

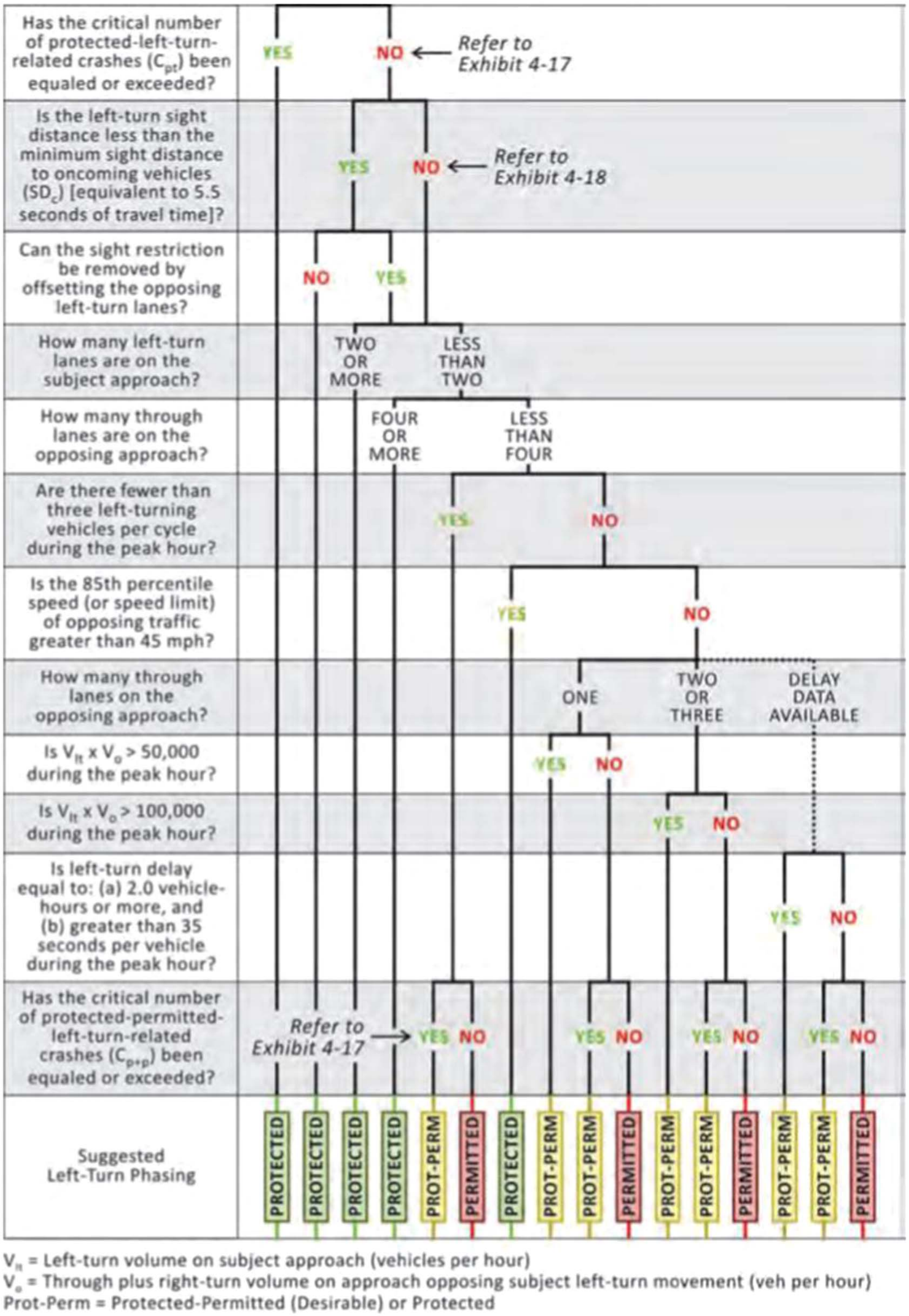


Fig. 4. Flowchart part 1. (Data from Lozner et al. 2015.)

multiple representations relate to the representation used by participants?). Visualization-based analysis allowed us to investigate many aspects of eye-tracking data in an explorative and qualitative manner, and served as the basis of further statistical analysis (Blascheck et al. 2014), as described below.

Grouped Box Plots

Grouped box plots are a quantitative tool that is commonly used in eye-tracking data visualizations (Hornof and Halverson 2002). These plots were used to investigate the first research question. Grouped box plots were used to visualize all fixation points for every participant at each representation separately. The reported choice of representation recorded from the reflective interview was overlaid on the VA data. We explored patterns between representation choice and assigned VA. Although professionals and students were plotted as separate groups, comparable qualitative observations (differences in pattern and complexity) were made on the plots.

Kernel Density Plots

Interactions between total and average fixation durations (in seconds) for each participant were visualized for two groups

Exhibit 4-17

Number of Left-Turn Movements on Subject Road	Period during which Crashes Are Considered (Years)	Critical Left-Turn-Related Crash Count (Crashes Per Period)	
		When Considering Protected-Only (Cpt)	When Considering Protected-Permitted (Cp+p)
One	1	6	4
	2	11	6
	3	14	7
Two	1	11	6
	2	18	9
	3	26	13

Exhibit 4-18

Oncoming Traffic Speed Limit (Miles Per Hour)	Minimum Sight Distance to Oncoming Vehicles (SDc) (Feet)
25	200
30	240
35	280
40	320
45	360
50	400
55	440
60	480

Adopted from "Signal Timing Manual", NCHRP, Second Edition, 2015

Fig. 5. Flowchart part 2. (Data from Lozner et al. 2015.)

(professionals and students) and three representations (equation, graph, and flowchart). Kernel density plots were used to classify the gaze pattern of each participant. Frequency and duration of gaze for participants provided an opportunity to group them for further comparison. This approach allowed individual participants to be visualized, and their choice to be overlaid (white dots) with gaze pattern, providing information about cognitive attention assignment (second research question). In the density plot, the total fixation duration was plotted on the vertical axis, and the average fixation duration was plotted on the horizontal axis.

Bar Charts of Statistical Features

Bar charts with the statistical feature are commonly used to compare groups (Convertino et al. 2003). Three fixation-related parameters were plotted to categorize professional and student participants: total (and percent) fixation count, total fixation duration, and average fixation duration. These three factors are interdependent in terms of calculation, but collectively convey unique messages about the gaze patterns of participants. These charts were selected to identify patterns in attention assignment through VA information as part of the second research question.

Quantitative Analysis

Visualization tools provide not only qualitative findings but also guidance on which factors are relevant to input in quantitative analyses. These analyses were designed to investigate how VA varies across representations for professionals and students (together and separately) as the third research question. Statistical methods were developed based on the work of (Pavlović and Jensen 2009) for statistical comparisons of eye-tracking data, and the work of (Voßkühler et al. 2008) for statistical inferences. Statistical tools were applied step-wise. Normality tests were performed. The Kolmogorov-Smirnov (KS) test for normality was selected to handle the unequal number of samples (Fasano and Franceschini 1987). Based on outcomes of non-normality, the dataset was tested for sufficiency on identifying statistical differences in VA received by three representations in two groups separately using the Kruskal-Wallis test of variance. This is a nonparametric test that can capture non-normality and uneven sample size (Dupont 2014). Based on the significance in difference, pairwise comparisons were constructed to identify the ranking of representations based on VA data and how that varies between professionals and students.

Normality Test

A two-sample KS test for normality was performed on fixation data separately for professionals and students, which revealed that total fixation duration (in seconds) was not normally distributed. At a 5% level of significance, the p-values were less than 0.05 (0.00, 0.00), coefficient of variation (CV) were negligible (0.0287, 0.0212), and K-statistic (0.5398) was the same for all groups. All three parameters provide strong evidence for non-normality.

The data collection methodology was designed to capture VA through eye tracking and the cognitive process of problem-solving through reflective interviews. Eye tracking provided a physiological manifestation of attention (i.e., fixations, saccades), whereas the reflective interviews represented the conscious assignment of cognition on specific problem elements. The analytical and quantitative analysis of collected data was designed to first, find patterns in the relationship between VA and cognitive assignment of attention and second, compare problem-solving techniques of professionals and engineering student participants.

Results

Professionals and engineering students solved the same problem while being provided with identical information and representations. The following results are presented to be consistent with the methodologies described above and address our specific research questions.

Allocation of Visual Attention

Fixation points for each participant were plotted using a grouped box plot according to representation (equation, graph, or flowchart). There were three possible choices: choosing only one representation (marked as a diamond), choosing a combination of any two representations (marked as a circle between the two chosen representations), or choosing all three representations (marked as a triangle).

Among the 23 professional participants, most used only one (11 participants) or two representations (10 participants); two professionals used all three representations. Among those who chose only one representation, eight used the flowchart, and three used the graph. Four professionals used the equations in conjunction with the flowchart or graph. The most commonly used representations were the flowchart (19 participants) and the graph (14 participants).

Among the 14 student participants, 11 chose only one representation (nine flowchart, two graphs), three used two representations (flowchart and graph). No student chose all three representations, and no student chose the equations. Two participants chose only the graphs. Two students reported familiarity with just the equation but did not use it in practice. The summary of representation choices is presented in Table 2

Compared with students, professionals typically had higher average fixation durations for their chosen representation, except for two professionals who chose the graph (Fig. 6). When a professional participant chose to use a combination of two representations, the sum of their average fixation duration on these two

Table 2. Summary of choice of representations

Representations	Professionals	Students
Equation	0	0
Graph	3	2
Flowchart	8	9
Equation*graph	1	—
Graph*flowchart	8	3
Flowchart*equation	1	—
All	2	—
No. of Participants	23	14

representations was higher than their average fixation duration on the representation that was not selected.

For students, the average fixation duration associated with their chosen representation, when only one of the three representations were chosen, displayed a nonhomogeneous trend: choice alone did not necessarily indicate that more attention was allocated to the representation (Fig. 7). However, the sum of the average fixations for multiple representations (combination of two or all three) was higher than the average fixation on the remaining unchosen representation.

The variety of choices and associated total and average fixation durations displayed by professionals compared with students indicates a diverse approach and strategies by professionals. When grouped based on representation, grouped-box plots for students showed multiple distributions on one representation. This result indicates that student participants discontinued gazing on that specific representation and returned later after some amount of time, thus producing a new discrete distribution of fixations.

Professional participants showed higher average fixation duration on their representation of choice, whereas this trend was not observed for students. For professionals, the flowchart was most commonly used, and the equation was the least, with the graph between those two choices. A similar trend was established from the grouped box plots for students. Although only six professionals of the 37 participants chose to use the equation, the average fixation duration on the equation was the highest among the representations. Thus, even if participants did not choose to use the equation to solve the problem, they attended to it visually.

Considering the use of multiple representations to solve the problem, professionals (52%) chose a combination of representations more than students (21%), whereas students tended to use one representation to solve the problem, most often selecting the flowchart. Some students showed a discrete gaze pattern, which was not observed in professional participants. This analysis helps address the first research question: How does the allocation of VA across multiple representations relate to the representation used by participants?

Trend Analysis of Statistical Features

Understanding where participants look can lead to a better understanding of how participants are perceiving and planning to solve a problem. Therefore, we next compared descriptive statistics between groups. Compared with professionals, students had a higher average total fixation counts for all five AOIs (Fig. 8). The definition, equation, and graph received low numbers of fixations for both groups, whereas the flowchart had the highest number of fixations. This result may be partially attributed to the fact that the flowchart covered a large portion of the problem layout and had more text than other AOIs. In addition, the flowchart was selected and used by participants.

Total fixation duration was lower for students than professionals, but fixation count showed the opposite trend, indicative of the shorter gazes of students. The total fixation duration on the definition, equation, and graph was marginally higher for students. The total fixation duration for the flowchart was higher than for any other AOI and was highest for professionals. Compared with students, professionals looked at the flowchart for an extended period every time they fixated on it. Compared with professionals,

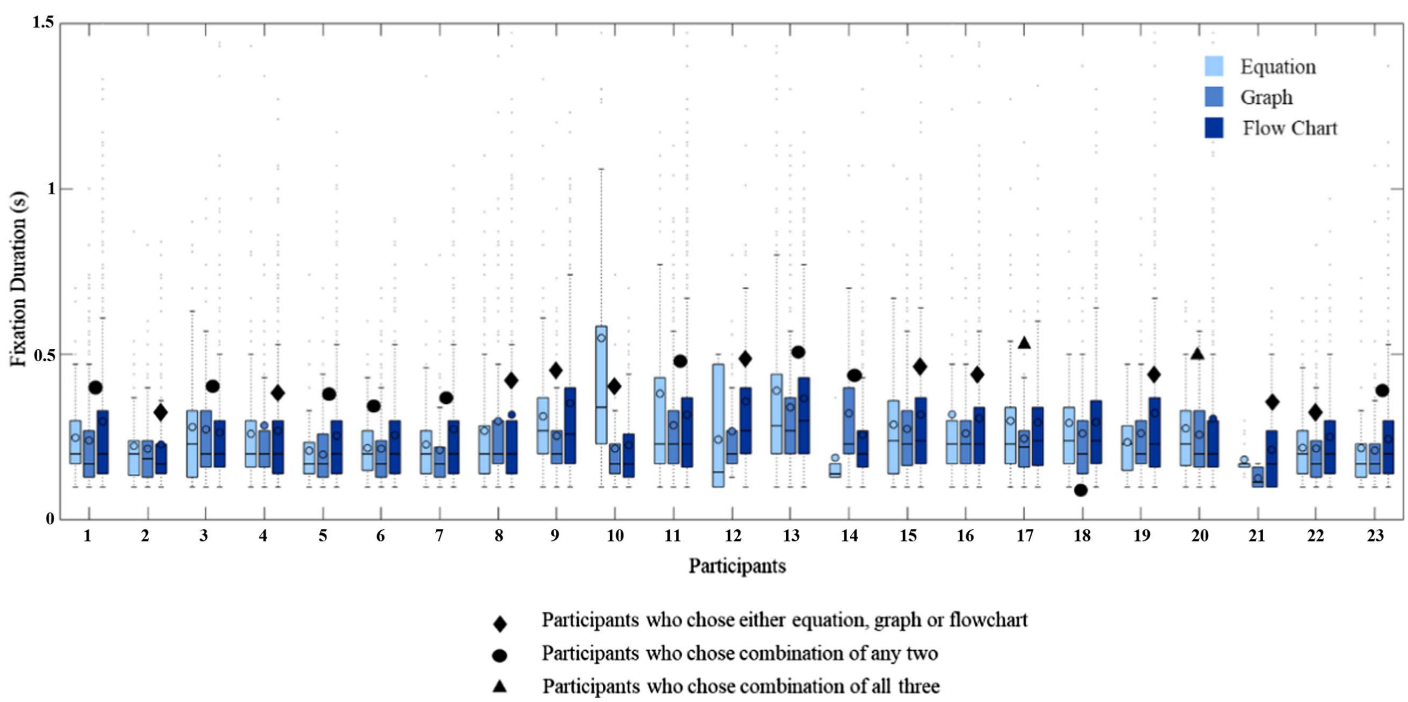


Fig. 6. Fixation duration(s) with choice of representation for professionals.

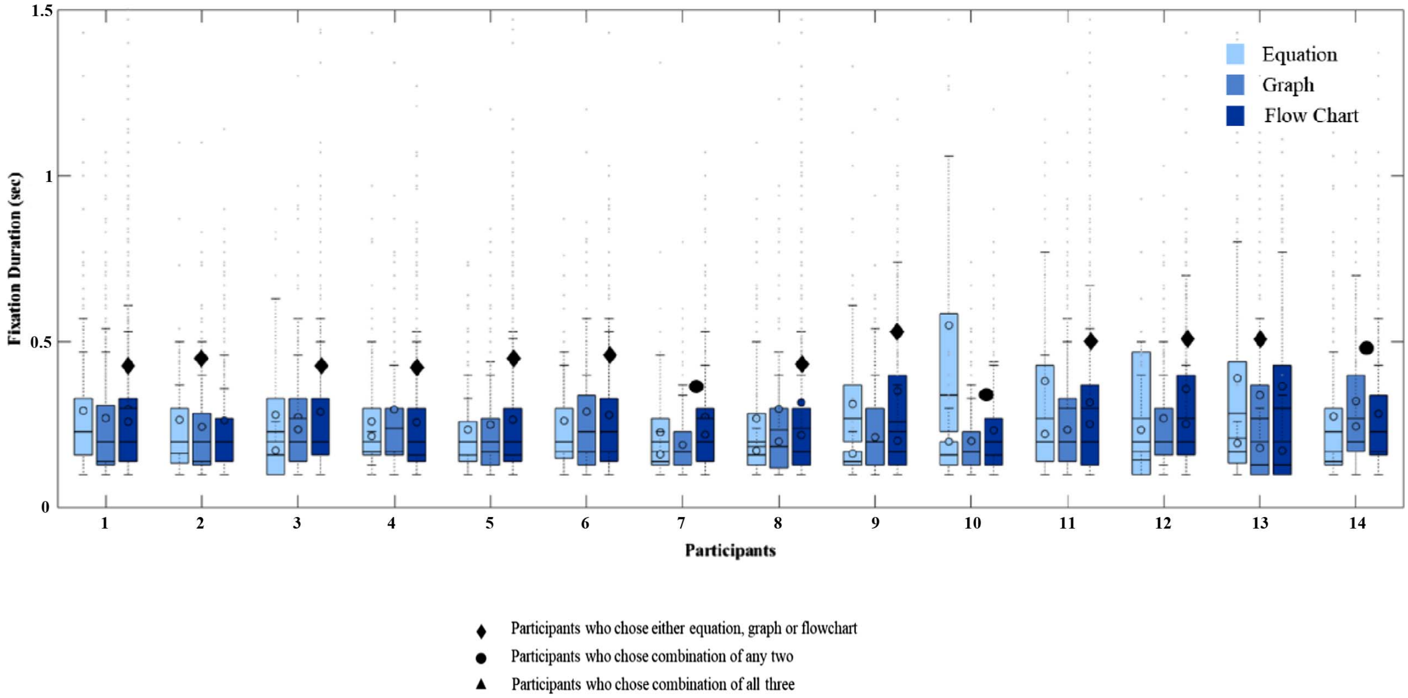


Fig. 7. Fixation duration(s) with the choice of representation for engineering students.

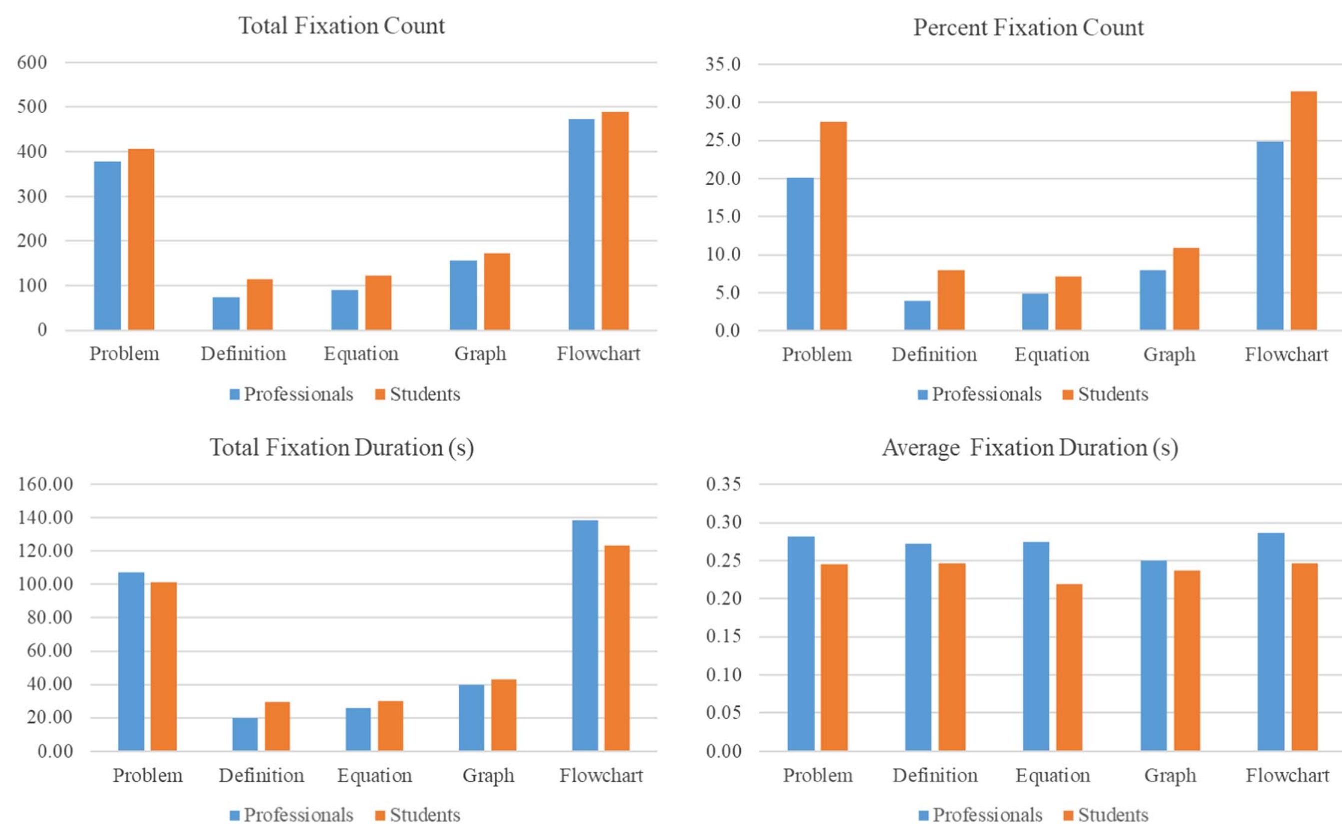


Fig. 8. Comparison of descriptive statistics between professional and student participants.

students had shorter average fixation durations (this parameter reflects the relationship between fixation count and total fixation duration). Considering that the fixation count showed the reverse trend, this result indicates that the VA of students comprised shorter gazes. Students looked more frequently to AOIs, but the total duration of each glance was less. Statistical analysis of VA features is presented in the evaluation of differences in the visual attention subsection.

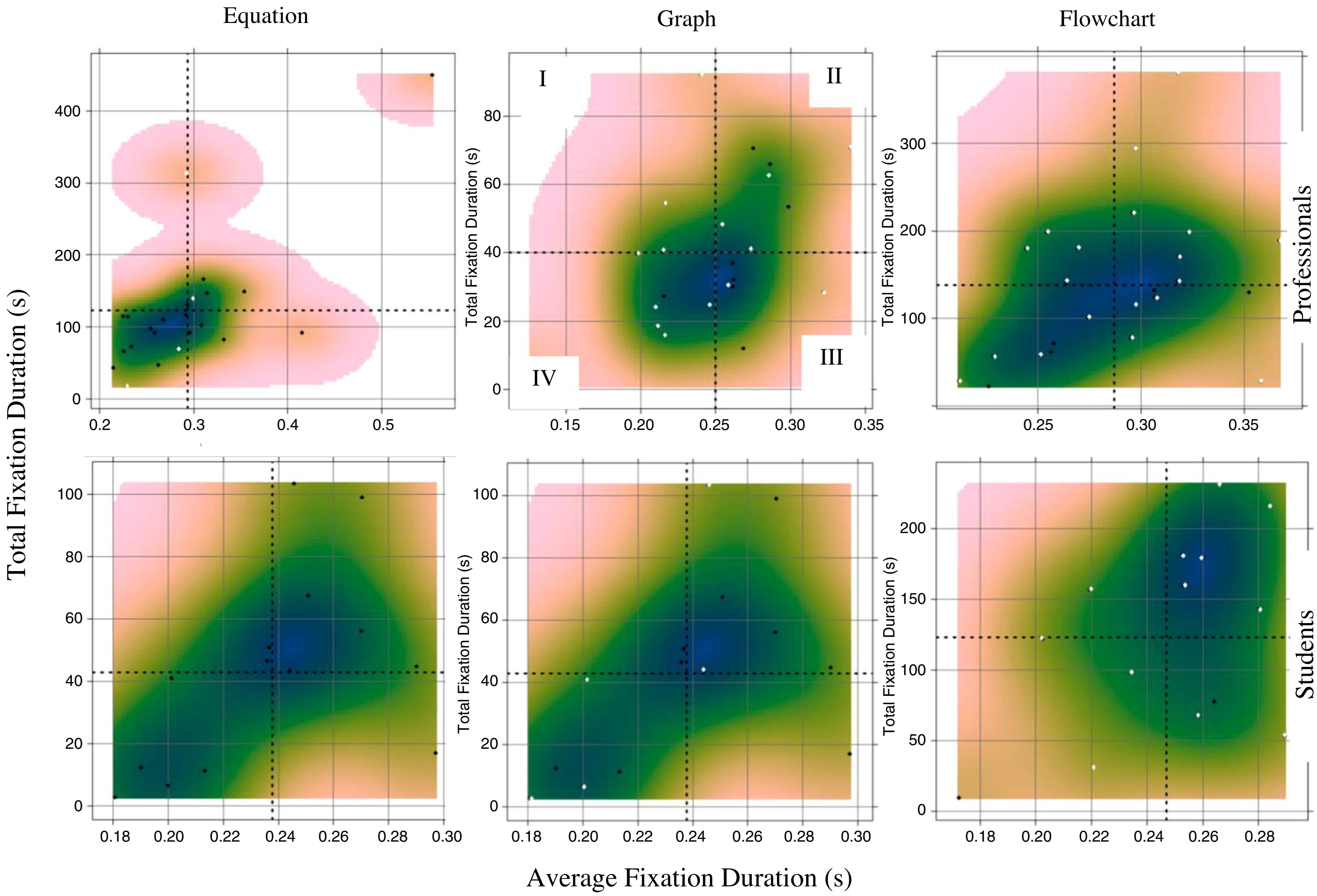


Fig. 9. Kernel distribution plots of equation, graph, and flowchart for professionals and students. Scales of these plots are not consistent because they were selected to highlight the center of density of each map.

Gaze Pattern Distribution

To investigate the second research question, Kernel density distribution plots were generated to qualitatively classify the observed gaze patterns of participants and how they assigned the majority of their attention (Fig. 9). Every participant looked at all three representations for some time. For professionals, the highest density (center) was near the mean intersection of average and total fixation durations, and attention was focused around this intersection. By contrast, students had a wider spread of density distribution but also multiple localizations of density. For students who did not select the equation or graph to solve the problem, VA was restricted to quadrants II and IV. Quadrant II describes participants who spent more time fixating on this AOI and had total fixation durations consisting of longer gazes. Quadrant IV describes participants who spent less time on this AOI but shorter individual fixations or gazes.

Completion Time

Professionals, on average, spent more time (18.7 min) solving the problem than students (11.6 min). Professionals allocated more VA off-screen than students. As the problem was open-ended, there were opportunities to make assumptions and judgments. Professionals made several assumptions, such as the presence of an exclusive left-turn bay on all four approaches (34%), left-turn bays on north-south approaches (28%), changing lane configuration that allows left-turn maneuvers from the left-most lane (21%), and as drawn design (17%). Only two students (14.3%) documented assumptions related to exclusive left-turning bays. This analysis contributes to the second research question regarding assignment and distribution of cognitive attention through the use of the conceptual framework and long-term memory and their difference for professional and student participants.

The Correctness of the Solution

As mentioned, the problem participants solved was a design problem related to the provision of left-turn protection at a signalized intersection. Given the level of specificity in the problem statement, the correctness of the solutions varied based on assumptions made. Left turn protection on the E-W direction was warranted, and all participants reached this conclusion. Protected phasing, protected-permitted phasing, adding a dedicated left-turn lane, and adding a middle turning lane were some assumptions made by professionals. In several cases, using knowledge from their practice, professionals recommended protection in both directions. Students either proposed a protected phase, without lane reconfiguration or proposed protected-permitted phasing. Only two students documented the necessary assumptions.

Evaluation of Differences in Visual Attention

Statistical features indicate that different magnitudes of VA were allocated to different AOIs. A normality test revealed the non-normality of the dataset. This section reports the sufficiency of the dataset to capture statistically significant differences. Nonparametric tests were explored to test the difference in the fixation duration distribution. The ranking-based Kruskal-Wallis test was selected to deal with non-normality and uneven sample size. The dataset captured the question of whether there was a statistically significant difference between total fixation durations of professionals and students at a 95% level of confidence. The result indicated that a statistically significant difference existed, with p-value $(0.000) < 0.05$, $\chi^2 = 50.81$.

As a part of the third research question, it was hypothesized that there may be a statistically significant difference in total fixation durations received by three contextual representations. Professional and student datasets were tested separately. For professionals, based on the p-value (3.42×10^{-9}) and χ^2 (48.2), it was concluded that there were statistically significant differences in total fixation durations between the equation, graph, and flowchart. When this test was repeated on students, statistically significant differences in total fixation duration were observed between the three representations at the 95% confidence level (p-value $= 1.48 \times 10^{-7}$, $\chi^2 = 31.45$).

To explore the magnitude of differences between representations, pairwise comparisons were performed. Table 3 compares the differences in total fixation durations between representations for professional participants.

The difference between the equation and graph was significant, with the equation having a higher median fixation duration. There was a statistically significant difference between the graph and flowchart, with the flowchart receiving greater total fixation duration. No significant difference was observed between the equation and flowchart. Therefore, the preference of professional participants on total fixation duration was ranked as flowchart/equation and graph.

Table 4 presents the magnitude of differences between representations for students, as derived from the pairwise comparisons in the Kruskal-Wallis test.

All three pairs were significantly different from each other. Equation and graph had a significant difference in total fixation distribution with the graph. A similar observation was made for the equation and flowchart, wherein the flowchart received a higher total fixation duration. Between graph and flowchart, the flowchart received more total fixation duration.

Repeating the test on the two datasets separately, a difference in total fixation duration between representations was found. The Kruskal-Wallis ranking test was applied to the combined dataset of professionals and students to test how total fixation duration for each representation varied (Table 5). The results showed that professionals spent significantly more time looking at the equations, whereas students spent more time looking at the graph. No statistically significant difference was noted for the flowchart between the two groups.

In summary, the dataset was sufficient to capture statistical differences. Professionals assigned greater total fixation duration on the flowchart and equation over the graph. No difference was noticed between the equation and flowchart. Students ranked the flowchart, graph, and equation in that order from most to least preferred. Professionals spent more time attending to the equation than students. The pattern reversed for the graph and flowchart.

Table 3. Total fixation duration(s) on representations for professional participants

Group 1	Group 2	Difference (1–2) (s)	p-value
Equation	Graph	248.3 (4.1 min)	0.000
Equation	Flowchart	−223.7 (−3.7 min)	0.998
Graph	Flowchart	−675.0 (−11.25 min)	0.000

Table 4. Total fixation duration(s) on representations for student participants

Group 1	Group 2	Difference (1–2) (s)	p-value
Equation	Graph	−377.8 (−6.3 min)	0.012
Equation	Flowchart	−501.9 (−8.4 min)	0.000
Graph	Flowchart	−268.8 (−4.48 min)	0.020

Table 5. Difference in total fixation durations on each representation between professionals and students

Professional	Students	Difference (professionals and students)	p-value
Equation	Equation	328.65 (5.5 min)	0.000
Graph	Graph	−483.49 (−8.1 min)	0.028
Flowchart	Flowchart	−256.12 (−4.3 min)	0.998

Discussion

This dataset is novel based on the performance measures collected and the number of participants in the transportation engineering education realm. For statistical significance, 15–20 participants are sufficient for eye-tracking studies. In this study, the 37 participants produced more than 15,000 fixation data points. The fixation threshold was set at 0.1 s, a value sufficient to capture all fixation categories. In the transportation engineering education domain, this volume of data is unprecedented. Data from 23 engineering professionals and 14 engineering students were analyzed to explore differences between experts and novices in planning, assigning VA, and making assumptions while problem-solving.

According to the fixation-point data distributions (Figs. 6 and 7), professionals assigned higher and continuous VA on their chosen representation. By contrast, students surveyed all representations nonuniformly. Fig. 8 shows homogeneity in the visual attention of professionals and variation among student participants. These results support previous findings from the literature (Hagerty et al. 2002; Kokotovich 2008) that novice participants went back and forth between representations even though most of them used only one representation. This could be indicative of a challenge in deciding which information is pertinent to complete a task in the student group.

Professionals used a combination of representations more often than students. 52% of professionals and 21% of students used a combination of representations. Literature suggests that professionals are likely to use a combination of multiple representations than students (Hagerty et al. 2002), and this finding was corroborated by the present study. Students tend to focus on one representation or a subset of it rather than making use of multiple presentations the same as Schwonke et al. (2009) found. When this finding was combined with assumptions made by professionals and lack of assumptions made by students, a further observation relating to deeper engagement and presence of strategy with the problem and representations was made.

Compared with professionals, students had a higher frequency of fixations, and each fixation was of a shorter duration (lower average fixation) (Kasarskis et al. 2001). Thus, students needed to look at the representations more often than professionals but spent less time on each look. This finding corroborates the notion that students struggle to retain information in their short-term working memory (Gegenfurtner et al. 2011) and need to have more looks or gazes on the information than professionals. However, the small-duration gazes indicate that a smaller volume of information could be extracted by students, in contrast to professionals. Aforementioned findings, when combined, provided evidence that there is a difference in problem-solving behavior among professionals and students and that is represented in their visual attention behavior, which answers the second research question of this article.

Professionals took longer to solve the problem than students. This is in contradiction to literature that suggests professionals take less time to solve a problem with greater accuracy (Tsui 2003). However, an open-ended design problem called for participants to assign boundary conditions and make assumptions. Professionals assumed the geometric design of the road, whereas this assumption was not observed in student interviews. In addition to that, the solution that when one approaches needs protection, but it is a practice putting protection in both directions was only suggested by professionals. Professionals spent more time looking away from the screen and representations and engaging in solving the problem. When considered in conjunction with the interview findings, it could be interpreted that professionals placed more importance on selecting the correct problem strategy than students. The kernel distribution plot indicated that professionals' gaze patterns were clustered around central properties (average and total fixation durations). In other words, most professionals acted similarly to each other, and there was less variation among them. The gaze pattern of students was noted to be scattered and did not follow a coherent trend. Similar average gaze patterns indicate that professionals cultivate a somewhat similar strategy to extract information but students search through the provided relevant and irrelevant information to determine pertinent information as corroborated by Kokotovich (2008).

In the statistical analysis, the question of statistical difference in visual attention between two groups were studied by comparing total fixation duration through a ranking-based test for an unequal non-normal sample. Using the Kruskal-Wallis test, it was observed that there is a statistically significant difference in visual attention between the two groups. As reported in reflective interviews, students chose to use representations in a different manner than professionals. As reported in reflective interviews, students chose to use representations in a different manner than professionals, resolving the first research question—patterns of visual attention were found to be different. Pair-wise comparisons were performed to evaluate the presence of additional difference. It was observed that professionals spend more time on the equation than students with no student reporting use of the equation. This agrees with the findings from the interview, that visual attention was not assigned to the equation by students as much as professionals. The same way, professionals spend less time on graphs when compared with students.

The use of the graph alone was not chosen commonly by professionals because it disregarded other factors. Students who chose to use the graph made the selection based on ease of understanding of a graphical tool. There was no statistical difference in fixation duration on the flowchart between two groups. Percentages of students and professionals using the flowchart are comparable; therefore, the lack of difference in visual attention for the flowchart confirms the outcome from the reflective interview.

For professionals, VA did not show any statistically significant difference between equation and flowchart. When observed beside the raw data, this lack of significance is logical. Professionals looked at the equation for a considerable amount of time. The equation was used by many professionals to clarify the concept as they are familiar with the terminologies, whereas the flowchart was used to reach the conclusions. As reported in the reflective interviews, a comparison of representations to another found that the difference in reported use of the graph and the flowchart is significant and the difference between the equation and graph. Professionals spent the most time referring to the equation and the flowchart, with the least amount of time being spent referring to the graph. This result is similar to self-reported choice of professionals as presented in Figs. 6 and 7. A rank ordering of the students' total fixation duration, starting with the highest duration would yeld: flowchart, graph, then equation. This agrees with the reported representations from the interviews, validating the statistical difference of the eye tracking data. This addresses the third research question by showing that the visual attention analysis is effective in detecting differences among groups.

The overarching question of reflection of domain knowledge on their problem-solving behavior was not measured quantitively in this study. Representations included in the study are empirical and included different traffic, geometric, and safety parameters. The formulaic representation, i.e., equations consider the volume of left turning and opposing through. The graph also includes the opposing speed but does not consider the opposing through volume. The flowchart considers the number of crashes, sight distance, traffic volumes, and speed limits and suggests which type of protective treatment should be applied. From the interviews, it was observed that students generally chose the representation with the most detail, the step-by-step process. Students did not report making any assumptions or setting boundary conditions. Professionals who did not regularly work with this type of problem, still reported making realistic assumptions. This could indicate that the presence of domain knowledge in one group leads to unique problem solving approaches when compared with a group that lacks specific domain knowledge.

Could all these findings be an indication of the fact that students are not being trained regarding the essence of design problems? As reflected in the results, students did not make use of multiple representations or make any assumptions when solving the design problems. These two findings should encourage instruction that promotes design solutions scaffolded with multiple representations. How a problem is translated into real-life seems to be missing in students' conceptual framework. Our recommendation is not only to introduce transportation engineering students to the multiplicity of representations but also to introduce them to what ideas these representations encompass. Establishing a deep understanding of the domain may shed light on students on which factors are useful to solve a specific design problem (Ainsworth 1999). Then, only cohesive use of different tools to determine the best outcome will be possible (Gog et al. 2005).

This finding is similar to literature that suggests that students engage in solving a problem with more than the real-life implication of the problem itself (Boshuizen and Schmidt 2008). Searching for a method to solve *a* problem was the students' focus, whereas professionals engaged with *the* problem to produce comparatively more elaborate solutions that indicated a lack of conceptual framework associated with this subject matter among students.

This study found that professionals chose to use multiple representations more often than students and that was reflected in the recorded interviews and the visual attention. Strategies and approaches to problem solving can only be implied from this study, but all evidence suggests that there are differences between professionals and students for both of these dimensions. Professionals and students used representations differently. Students predominantly used one representation that was stepwise. Visual attention-based clustering revealed a similarity between professionals and dissimilarity between students indicating a lack of training to solve domain- specific problems. Students took less time to arrive at an answer; however, they omitted the documentation of assumptions and the use of multiple representations in their problem-solving process. We can develop educational experiences for students that are more in line with industry needs when we understand how industry trained professionals solve design problems, which was the primary goal of this study.

Implications

In practice-based domains like transportation engineering, the goal is to teach students how to solve real-world problems using industry accepted standards of practice. Therefore, how professionals analyze a problem and the tools they use to solve the problem, need to be understood robustly to train students effectively. This study contributed to this understanding by determining ways students deviate from professionals during problem solving. Students seemingly did not consider an intersection that they drive regularly, they solved an abstract problem using the most elaborate tool available. Their domain knowledge, exposure to the content of the problem (left turn at an intersection), use of multiple representations, making necessary assumptions—were some missing components of the student approach. Our understanding is that these findings suggest that students who participated in this experiment, did not engage with the domain and representations and they struggled with decision making.

Therefore, the way that engineering design problems and fundamental engineering concepts are taught in the classroom can be revisited. One example of this could be providing students with a variety of representations and resources early and often when solving design problems. This research indicated more practical experience in the field and physical demonstration can be proven beneficial. If experts approach problems differently by evaluating different contexts and solution resources more holistically, there could be value in providing opportunities for students to learn similar skills. By varying the methods students use to solve problems and providing additional reasoning for the use of those methods compared with others, students could gain valuable skills that help them navigate between resources more efficiently and effectively. The reasons for choosing one method over another could be motivated by factors that engineering practitioners face in the workplace. Future work related to these reasons could help support this implication and provide a better model for improving the problem-solving skills of engineering students.

Limitations

Due to the complexity of the relationship between visual attention and cognition, the results of this experiment should be interpreted through the context of this experiment. Whereas we believe that the methodology demonstrated in this experiment is transferable, it remains unclear if these results would be reproducible. The reflective interviews could have been more detailed in their documentation (adding more demographic information, focusing equally on problem solving strategy and choice of representation, years of experience, and experience of solving this particular problem) of the problem-solving steps and strategies demonstrated by the participants. Future research should consider years of experience, familiarity, field of expertise, and detailed domain expertise can be added to the statistical model to more accurately document the difference between experts and students. In addition, future research should further differentiate expertise throughout transportation curriculum and practice using eye tracking, interviews, or other appropriate methods.

Data Availability Statement

Some or all data, models, or codes that support the findings of this study are available from the corresponding author upon reasonable request.

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