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# Complexity, Performance, and Search Efficiency: An Eye-Tracking Study on Assembly-Based Tasks among Construction Workers (Pipefitters)

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**Abstract:** Past studies have used eye-tracking glasses to analyze people's perception of visual stimuli, usually regarding wayfinding, safety, or visual appeal. Some industries, such as the automotive industry, studied the effects of visual stimuli on task completion. However, the architecture and construction industries have mainly conducted eye-tracking experiments with surveys or search tasks instead of performing a task. This paper uses eye-tracking glasses to analyze people's perception of visual stimuli while completing tangible tasks that simulate real-world applications. This research studies how people look at visual stimuli that influence their ability to interpret drawings with varying degrees of complexity, assess task completion performance, and inspect how people search for information. Twenty pipefitters wore eye-tracking glasses to record their eye movement patterns while completing a model pipe spool assembly. The eye-tracking glasses and Visual Eyes software measured visit metrics, fixations, fixation durations, convex hull coverage, assembly time, rework, and errors. Unlike previous studies, convex hull areas are calculated and used to measure search efficiency. This research found that people interacted more frequently with more complex visual stimuli but did not necessarily require more time to complete a task. People with lower search efficiency visited the drawings more frequently than people with higher search efficiency. People with higher search efficiency made fewer mistakes, redid less work, and completed tasks quicker than those with lower search efficiency. Search efficiency was found to be a good predictor of task performance.

**Keywords:** eye-tracking/eye tracking/eyetracking; gaze; fixation; convex hull; task completion; complexity; visual search ability; productivity; drawings; construction



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## 1. Introduction

Many industries, including construction, have used eye-tracking to understand how a person looks at visual stimuli and processes information. Construction workers are expected to understand and build according to the information specified in the drawings. However, the construction industry has persistently struggled with skills shortages [1–6]. Some construction workers are asked to perform tasks without formal training in extracting information from construction drawings. This research will help the industry by identifying how drawing complexity influences construction workers' interaction with drawings, i.e., should drafters adopt new techniques to cater to both the more and less experienced workers? Additionally, this research will help the industry by identifying how complexity influences construction workers' performance in completing a task. Finally, this research will describe the relationship between search efficiency and performance to understand how construction workers look at the drawings and process information concerning their on-site performance.

### 1.1. Eye-Tracking

Previous research established eye-tracking as an appropriate tool to measure how a person interacts with visual stimuli. Figure 1 and Table 1 summarize the most pertinent eye-tracking terminology. Eye-tracking software allows researchers to visually map out the exact points, commonly referred to as gaze points, a person is looking at on a visual stimulus [7]. Eyes do not necessarily look directly at the precise point of interest but instead, rely on a group of gaze points to comprehensively understand that interesting visual point. A group of gaze points, or fixation points, indicate the location the person is looking at [8]. Researchers have used fixation counts and durations to understand what the person is looking at and how long they are fixating on that point. Higher fixation counts and durations may imply a person is having greater difficulty in processing information either due to a complex task [9], complex stimulus image [10], or even differences in mental cognition [11,12]. Gaze points may offer too much detail making it harder for researchers to find a pattern, and glances may offer too little insight into how a person is processing information. Researchers have used scanpaths, "a sequence of alternating saccades and fixation points" [8], to understand how a person gathers information on a stimulus image. Convex hulls are the "areas covered by the scanpath" [8]. Convex hulls provide a more accurate depiction than a scanpath of how a person gathers information on visual stimuli. It may be helpful to think of scanpaths as a line connecting points while convex hulls engulf the points and lines with a buffer to help researchers visualize the areas a person is focusing on. The smaller the convex hull, the better a person's search efficiency or ability to interpret information.

**Table 1.** Eye-tracking terminology.

| Terminology | Definition |
|---|---|
| Area of Interest (AOI) | The boundary defining the most important parts of a visual stimulus [8]. In this research, the pipe spool assembly components are the AOI. |
| Glance | A quick look at visual stimuli [13]. |
| Fixation | A grouping of gaze points that are relatively close to each other (20 to 50 pixels) within a short timeframe (200 to 300 ms) [8]. |
| Gaze Point | The point where the eyes are looking at a certain time on a visual stimulus [7]. |
| Saccade | The transition from one fixation to another [8]. |
| Convex Hull | The area of a visual stimulus that was of interest to the viewer. Convex Hulls focus on the fixation points and saccades of interest to the researcher [14]. |
| Visit | The number of times a pipefitter visited an assembly drawing. |

Researchers have studied the effects of complex visual stimuli in many industries, including but not limited to advertising [15], the automotive industry [16,17], computer software and website interfaces [9], and cartography [18,19].

### 1.2. Architecture, Urban Design, and the Built Environment

In theories of the built environment, researchers have found that people cling to the edges of a building, road, or other environments and then flow in and explore [20]. Edges help people orient themselves within a space. In the same sense, familiarity increases people's confidence in assessing visual stimuli. Because people gravitate towards familiarity or predictability, any odd or unexpected element will garner more attention or time to process the visual stimulus. The researchers also indicated Thatcherization as an example of this phenomenon, where the unexpected visual stimulus received more attention than the predicted visual stimuli. When a visual stimulus is considered familiar or predictable, people do not need to exert a lot of mental energy to understand the visual stimulus. This decrease in mental exertion is because the brain gravitates towards "organized complexity" to look for meaning in the visual stimulus. When people view an image without finding something familiar to anchor their gaze on, it increases the mental burden on the individual. People will focus on every detail of the visual stimulus to try to make sense of the general purpose. However, when the visual stimuli follow a clear and predictable order, the mental load on people processing the visual stimulus decreases significantly.

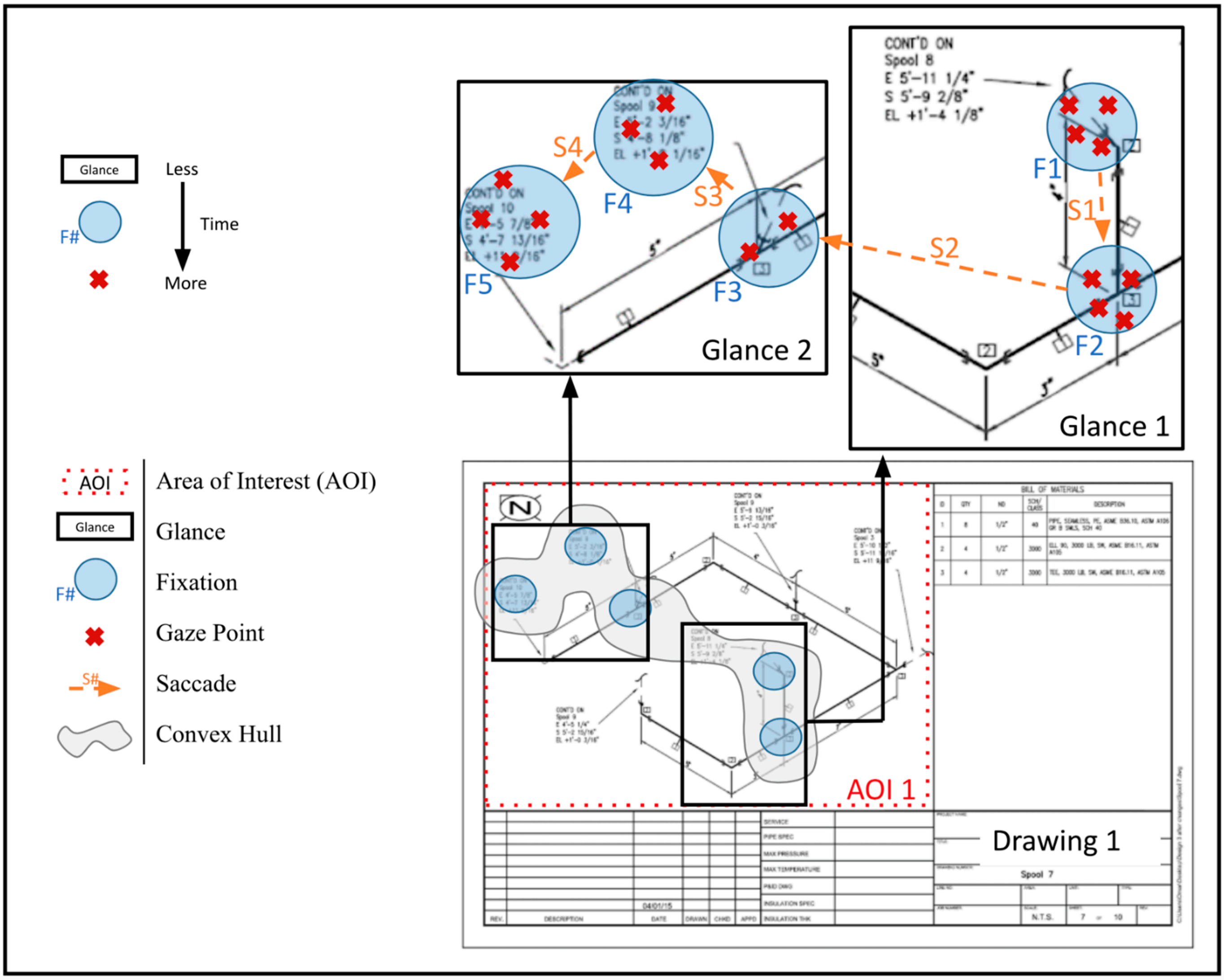


**Figure 1.** Illustrated eye-tracking terminology (inspired from [8]).

Other researchers have used eye-tracking to gauge the general public's perception of windows on traditional and modern buildings. The researchers used 3M-VAS (visual attention software) to analyze thirty decades worth of eye-tracking data [21]. The study investigated how architectural designs influence the "unconscious" and "conscious" minds. When people encounter common or expected visual stimuli, people "unconsciously" feel welcome. However, the current architecture practice is very rigid with their design elements and guidelines that do not necessarily agree with peoples' "unconscious", as neuroarchitecture is still a growing science. Design should, in essence, consider how people view and interact with the visual stimulus. The researchers also studied "cognitive entanglement", which is how viewers may group groups of elements.

The concept of cognitive entanglement can improve how drafters design construction drawings and how easily construction workers can learn or access the necessary information. Essentially, this concept builds off the need for familiarity when looking at drawings by creating congruency and fluency between the design elements. People can quickly collect the necessary information when they are familiar with a concept or pattern. Consequently, people unfamiliar with a concept or pattern will have scattered gaze points.

### 1.3. Construction Engineering

A previous research study consisted of conducting literature reviews and administering surveys to improve engineering drawings [22]. The survey respondents ranged from managers to project engineers. The projects included in the survey included bridges, highways, buildings, airports, marine and port facilities, culverts retaining walls, and signs. The study emphasized communication issues between the owner, engineers, and contractors. Only some DOTs use colored drawings to make the drawings easier to understand [22]. The main issue with using color is that even if the DOTs produce engineering drawings in color, the drawings would probably be printed in black and white. One way to mitigate this issue is to use greyscale to differentiate the different elements, as designers are already using line weights to differentiate some elements.

AR and 4D modeling advances have been clearly established to document project progress and visualize project sequencing [23]. Despite the growing trend of using BIM technologies or the more advanced AR or VR, on-site construction workers are generally equipped with printed 2D drawings. Therefore, there is a critical need to evaluate the construction drawings' effectiveness and identify improvement areas. Specifically, studying this would enable researchers to advocate for changes in construction drawings' design standards or advise how to read construction drawings to increase efficiency. In reality, it would be a mixture of both options.

Researchers have provided construction workers with video tutorials about sequencing tasks [24]. The researchers based their instructional video content on accessibility, viewability, timing, duration, "describability", accuracy, completeness, ease to follow, pertinence, self-efficacy, and engagement. Designers could follow similar guidelines when drafting construction drawings to ensure that people with varying skill sets would perceive the information quickly. The study emphasized the communication issues between owners, designers, and contractors, especially how some information may fall through the cracks. Clear construction drawings would alleviate the reliance on these unreliable communication chains. However, researchers are just scratching the surface of understanding exactly how people look at construction drawings and search for the relevant information to complete the task required.

Other researchers used the IKEA Furniture Assembly Environment to model furniture assembly sequencing for robotic intervention [25]. The environment is highly customizable to mimic real-world scenarios with options to control lighting, textures, and background. The program gives users the option to use one of six robots. Some researchers have adopted the IKEA-style build-as-you-go approach for assembly tasks, which may be an option for future researchers to consider studying how people view and search for information. The possible issue with applying this technique is that the sequencing of construction tasks is highly dependent on many factors, such as contract type, scheduling limits, staff constraints, and regulations.

In a different study, 38 students were asked to sequence the elements of a framed wall using 2D drawings or augmented reality (AR) [26]. The group of students with 2D drawings was asked to manually write down the construction sequence of the framed wall on a worksheet. The group of students with augmented reality was asked to use voice commands to sequence the elements of the framed wall. The study found that participants spent less time when provided 2D drawings than AR. Unfamiliarity with AR technology may have contributed to longer task completion times. However, students with AR displayed signs of critical thinking and were more likely to identify and fix their errors. These results indicate that there needs to be more connection between construction drawings and comprehension.

By understanding exactly how people search for information, researchers and designers can redesign construction drawings to aid in sequencing logic.

*1.4. Differing Information Formats, Spatial Cognition, and Pipefitter Performance*

Several studies investigated the effects of differing engineering formats on spatial cognition and task performance. In 2016, researchers investigated the effects of differing engineering formats on spatial cognition [27]. Fifty-four industrial pipefitters were tasked to assemble a single pipe-spool assembly using either 2D drawings, 2D drawings supplemented with a 3D CAD model, or 2D drawings supplemented with a physical 3D model. The pipe-spool assembly model was on a 1/12 scale with 12.5 mm (1/2 in) PVC pipes. The participants ranged from young apprentices with one year of experience to seasoned veterans with 47 years of experience. The pipefitters were evaluated using five-minute ratings to evaluate their efficiency by assigning the observations to direct work, indirect work, or personal time. The researchers also measured the number of errors the pipefitters made during assembly. The study's main limitation was that the model was relatively simple and did not account for complexity when assessing spatial cognition. The study found that people who viewed 2D drawings performed significantly worse than those with a 3D physical model or 3D CAD model.

Additionally, the researchers found that people with lower spatial cognition performed significantly worse when looking at 2D isometric drawings than people with higher spatial cognition. The supplementation of 3D drawings helped people with lower spatial cognition to perform better. The researchers suggested that future research should focus on understanding exactly how people view and search for information to perform tasks. A noteworthy quote from their research emphasizes the importance of "having the right information at the right time in the right format".

Building off the previous research, researchers used eye-tracking glasses to assess the spatial cognition of 45 industrial pipefitters using different information formats [28]. The pipe-spool assembly model was significantly more complex in this study than in the previous study. The pipe-spool assembly had the same scale of 1/12 with 12.5 mm (1/2 in) PVC pipes. The pipefitters were evaluated using five-minute ratings to evaluate their efficiency by assigning the observations to direct work, indirect work, or rework. Eye-tracking glasses were used to monitor fixations, sequence of fixations, fixations per area of interest (or gaze plots), and fixation spatial density (or heat maps). The results were then aggregated for analysis. Even though the analysis only involved 12 participants, the analysis was completed in a future study, which is explained below. The researchers suggested that future research should use more robust eye-tracking metrics to assess eye-gaze patterns properly.

Another paper continued the efforts of previous work by Alruwaythi et al. (2017) [28] by increasing the sample size to 60 industrial pipefitters, where 20 pipefitters were provided 2D isometric drawings, 20 were given 2D isometric drawings with 3D images, and 20 were given 2D isometric drawings with a 3D physical model [12]. Participants with only 2D isometric drawings performed the worst out of all the groups in terms of average fixation time and the average number of fixations. However, participants that used 2D isometric drawings with the 3D physical model had the highest number of revisits. Additionally, people with higher spatial cognition spent less time and had fewer fixation points than people with lower spatial cognition. The findings of this study proved that people with lower spatial cognition perform better when supplementing 2D drawings with 3D information. Mainly, their paper touched upon enhancing working memory to improve task performance. Their study found that information formats significantly influence eye gaze patterns. Despite people with lower spatial cognition having "longer fixation times and a higher number of fixations and revisits" when viewing 3D information, they successfully completed the task. The researchers suggested that improving information formats will improve task efficiency and effectiveness. The researchers indicated a gap in the body of knowledge to understand exactly how people look and search for information to complete the necessary tasks.

Another paper built off Alruwaythi et al.'s (2017) research [28] by inspecting how the 20 professional pipefitters that used 2D isometric construction drawings view, perform, and interpret information [29]. Convex hulls were used to inspect eye-gaze patterns. The researchers analyzed average convex hull areas and spatial cognition. The study found that people with more experience had lower convex hull areas. The researchers emphasized the need to further inspect why people with differing spatial cognitive abilities have different eye-gaze patterns. More importantly, the researchers suggested using a convex hull as a metric for search efficiency and inspecting how the different drawings range in complexity. Convex hulls would need to be modified to accurately portray eye gaze patterns, as suggested in previous research [7]. These recommendations are applied to the current research.

This research differs from Alruwaythi and Goodrum [12] and past research in three main ways. This work uses convex hulls as a search efficiency metric, evaluates the complexity of the drawings for each participant by objective criteria metrics, and evaluates task performance. This research uses eye-tracking technology to measure complexity, task performance, and search efficiency. The researchers hypothesize that as a visual stimulus or construction drawing complexity increases, construction workers will interact more frequently and require more time to complete a task than less complex drawings. Construction workers that visit a drawing more often and spend more time looking at a drawing are predicted to have lower task performance than construction workers that reference the drawings less frequently. Construction workers with greater search efficiency (lower average convex hull coverage) are predicted to perform better than pipefitters with lower search efficiency scores (higher average convex hull coverage).

## 2. Materials and Methods

This research design relies on the data and design of Alruwaythi and Goodrum [12]. Alruwaythi and Goodrum [12] used eye-tracking glasses to analyze the spatial cognition of construction craft workers against differing information formats (2D isometric drawings, 2D isometric drawings alongside a 3D model image, and 2D isometric drawings supplemented with an actual 3D model). The participants were 60 MEP professionals, mostly belonging to union chapters along the Colorado Front Range. The participants varied in age and industry experience, ranging from newly joined apprentices to seasoned professionals. The researchers administered card and cube rotation tests assessing participants' spatial cognitive abilities. The card rotation test assesses 2D cognitive abilities, while the cube rotation test assesses 3D cognitive abilities. The participants were asked to assemble a piping model using the information format provided by the researchers. Refer to Appendix A for the pipefitter and drawing data.

### *2.1. Participants*

For this study, the researchers focused on studying people that viewed 2D isometric drawings. A total of 20 industrial pipefitters were included in the dataset. The pipefitters ranged from 20 to 60 years of age, with 1 to 39 years of work experience in the construction industry (Table 2). The pipefitters were provided a set of ten isometric pipe spool drawings to assemble a pipe spool assembly model (Figure 2). They were provided precut $1/2''$ diameter PVC pipes and $1/2''$ diameter PVC fittings. The ten isometric drawings used in the experiments are shown in Figure 3. The pipefitters were free to look at the assembly drawings as necessary, and the task concluded when each pipefitter stated that they had finished assembling the PVC components.

**Table 2.** Pipefitter experience descriptive statistics.

| | Min | Mean | Max | Std. Dev. | Skewness | Kurtosis |
|---|---|---|---|---|---|---|
| Age (years) | 20 | 34.3 | 60 | 11.8 | 0.753 | −0.502 |
| Years of Industry Experience | 1 | 11.4 | 39 | 10.6 | 1.301 | 1.163 |

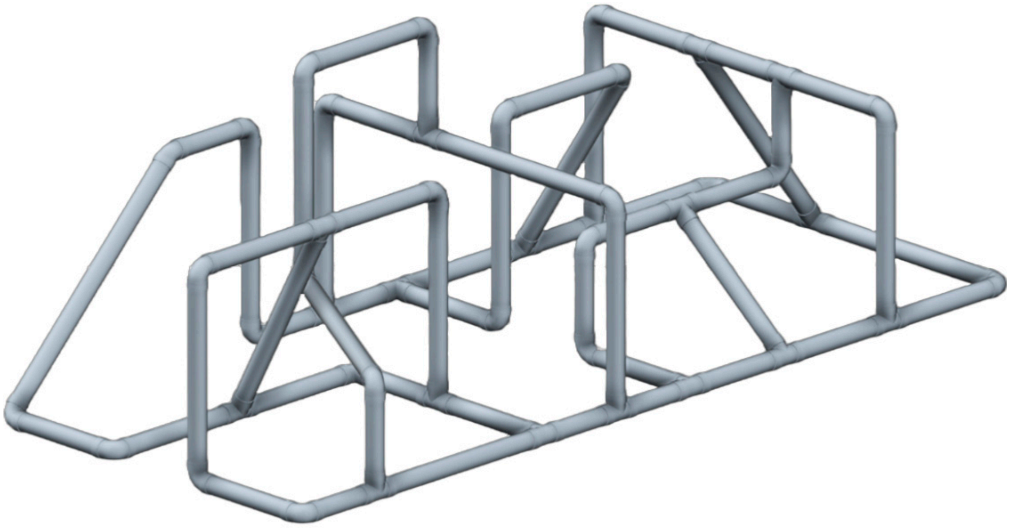

**Figure 2.** Completed pipe spool assembly model.

*2.2. Eye-Tracking*

SMI Eye Tracking Glasses 2.0 Wireless Analysis Pro from SensoMotoric Instruments Inc. Teltow, Germany and the accompanying "BeGaze" eye-tracking analysis software [30] were used for data collection. Before beginning the experiment, each participant was asked to view specified targets on reference images to calibrate the eye-tracking gaze data. For calibration, the researchers adjusted the gaze cursor to the participants' gaze points in the reference image. The BeGaze software did not offer some metrics that interest this research. Therefore, the researchers built an open-source website called "Visual Eyes" that compliments the BeGaze software to calculate differing metrics [31]. Most importantly, Visual Eyes calculates convex hull coverages for each of the ten drawings. Refer to Appendix B for instructions on incorporating BeGaze data with Visual Eyes.

The Visual Eyes web application incorporates the hull.js (v0.2.11) NPM package to compute the convex hull area for the fixation points recorded in each visit [32]. The dimensions of each stimulus image (assembly drawing) were measured in pixels, so the area of each stimulus image was measured in square pixels, the coordinates of each fixation point were measured in pixels, and the area of each convex hull was measured in square pixels. Dividing the area of each convex hull by the area of its associated stimulus image provides the convex hull coverage, which is a percentage Equation (1).

$$Convex\ Hull\ Coverage = \frac{Convex\ Hull\ Area}{Stimulus\ Image\ Area} \quad (1)$$

Each visit had an associated convex hull coverage, so each pipefitter had a distribution of convex hull coverages, and each assembly drawing had a distribution of convex hull coverages. In order to compare convex hull coverage between pipefitters and drawings, average convex hull coverages were computed. Convex hull coverage was used as a measure of search efficiency in this study.

A convex hull is a polygon that, by definition, requires a minimum of three non-collinear points to produce an area greater than zero. However, 950 of the 5052 recorded visits were so brief that they included only two fixation points and had a convex hull coverage of zero. These brief visits with zero convex hull coverage were omitted from all average convex hull coverage computations. The pipefitters had average convex hull coverages that ranged from 3.09% to 4.47%.

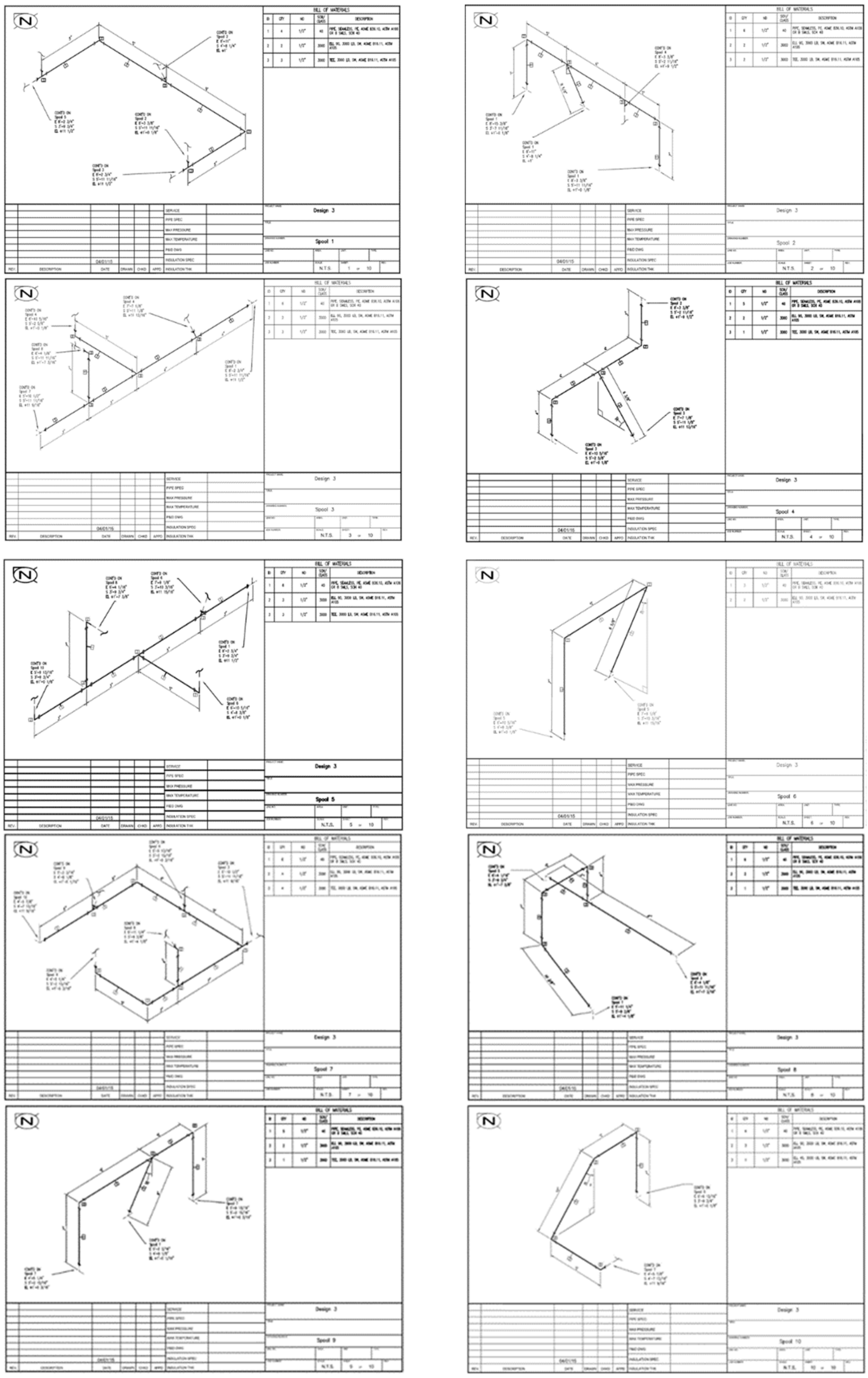

**Figure 3.** Pipe spool assembly drawings used in experiment (from top left to right, starting with Assembly Drawing 1 and ending with Assembly Drawing 10).

Researchers used convex hulls to measure search efficiency on search tasks. Kotval and Goldberg [33] used convex hulls for a search task. This research is a construction assembly task, which means it evaluates how a person looks for appropriate information to construct a pipe spool assembly. The authors hypothesized that people who look at a visual stimulus more frequently and for extended periods are less likely to find the appropriate information efficiently. Additionally, the authors hypothesized that people with larger convex hull areas are prone to making more errors than those with smaller convex hull areas.

### 2.3. Variables of Interest

This research studies the relationship between the following: 1—complexity and pipefitter interactions; 2—pipefitter interactions and search efficiency; 3—search efficiency and performance. Table 3 describes the metrics used for each variable of interest. Other researchers [21] made a great point to emphasize that gaze points and increased attention do not necessarily mean admiration or confusion. Context is important when deciphering eye-tracking data. The vastly differing visual contexts are why many researchers have used different metrics to gauge visual complexity. This paper defines complexity as the number of fittings, pipes, and references. These metrics provide objectivity and replicability to complexity.

**Table 3.** Definition of variables.

| Variables of Interest | Variables | Definition |
|---|---|---|
| Visual Complexity | Fitting Count<br>Pipe Count<br>Reference Count | Total number of fittings in an assembly drawing<br>Total number of pipes in an assembly drawing<br>Number of tags in a drawing that refer to a different assembly drawing |
| Pipefitter Interactions (Visit Metrics) | Visit Count<br>Average Visit Duration | Number of times a pipefitter visited an assembly drawing<br>Average time (s) each pipefitter spent per visit to an assembly drawing |
| Search Efficiency | Average Convex Hull Coverage | Polygon encompassing fixation points |
| Performance | Assembly Time<br>Number of Errors (# Errors)<br>Rework (%) | Time required to complete pipe spool assembly task<br>Number of errors in the completed pipe spool assembly<br>Proportion of time that a participant spent disassembling and reassembling components |

#—Number of Errors

The sample consisted of 20 pipefitters. Table 4 provides a descriptive summary of pipefitter data. On average, each pipefitter visited drawings 253 times and spent around 3.4 s on each visit. Pipefitters spent between 22 and 72 min completing the pipe spool assembly task with a maximum of 4 errors. The data are assumed to be normally distributed, as referenced by the skewness and kurtosis values.

**Table 4.** Descriptive statistics—pipefitters (N = 20).

| | Min | Mean | Max | Med | Std. Dev. | Skew | Kurt |
|---|---|---|---|---|---|---|---|
| Visit Count Per Pipefitter | 110.00 | 252.60 | 359.00 | 249.00 | 77.61 | −0.25 | −1.13 |
| Avg Visit Duration | 2.23 | 3.42 | 4.67 | 3.34 | 0.72 | 0.23 | −0.89 |
| Rework % | 0.00 | 8.87 | 19.28 | 8.78 | 5.44 | 0.15 | −0.86 |
| Assembly Time | 1334 | 2433 | 4314 | 2278 | 790.6 | 0.70 | −0.01 |
| # Errors | 0.00 | 1.20 | 4.00 | 1.50 | 1.24 | 0.50 | −0.67 |
| Avg Convex Hull Coverage | 0.031 | 0.045 | 0.071 | 0.042 | 0.01 | 0.99 | 1.06 |

#—Number of Errors

The sample consisted of 10 isometric pipe spool assembly drawings. On average, each drawing was visited 505 times, and the average time spent on each drawing was 3.32 s. The data are assumed to be normally distributed, as referenced by the skewness and kurtosis values in Table 5.

**Table 5.** Descriptive statistics—assembly drawings (N =10).

| | Min | Mean | Max | Med | Std. Dev | Skew | Kurt |
|---|---|---|---|---|---|---|---|
| Visit Count Per Drawing | 277.00 | 505.20 | 804.00 | 475.00 | 179.17 | 0.63 | −0.61 |
| Avg Visit Duration | 2.18 | 3.32 | 4.78 | 3.16 | 0.74 | 0.60 | 0.61 |
| Reference Counts | 2.00 | 3.70 | 6.00 | 3.50 | 1.34 | 0.33 | −0.85 |
| Fitting Count | 2.00 | 4.40 | 8.00 | 4.00 | 1.71 | 0.88 | 1.13 |
| Pipe Count | 3.00 | 7.10 | 12.00 | 6.50 | 2.81 | 0.36 | −0.77 |

## 3. Results

### *3.1. Complexity and Pipefitter Interactions (Visit Metrics)*

#### 3.1.1. Pipefitter Interaction (Visit Count) by Visual Drawing Complexity (Number of Fittings, Pipes, and References)

A Pearson correlation coefficient was computed to assess the linear relationship between pipefitter interactions (visit count) and the drawing complexity metrics (number of fittings, pipes, and references, respectively). The results suggest a positive correlation between pipefitter interactions (visit counts) and drawing complexity metrics (Table 6). These results indicate that as the number of fittings, pipes, or references on an assembly drawing increases, then pipefitters refer to drawings more frequently when compared to assembly drawings with less number of fittings, pipes, or references. Essentially, these results suggest that as assembly drawings become more complex, pipefitters require more visits to visualize and piece together the required information.

**Table 6.** Pearson's correlation (r)—pipefitter interaction (visit count) by visual drawing complexity (number of fittings, pipes, and references) (N = 10).

| | Pearson's Correlation (r) | *p*-Value |
|---|---|---|
| Fitting Count | 0.717 | 0.020 * |
| Pipe Count | 0.760 | 0.011 * |
| Reference Count | 0.861 | 0.001 * |

* Significant at the 0.05 level.

Linear regression was computed to assess the degree of complexity that predicts the number of times a pipefitter visits a drawing. It was found that fitting count, pipe count, and reference count significantly predicted the number of times a pipefitter visited a drawing (Table 7).

**Table 7.** Linear regression—pipefitter interaction (visit count) by visual drawing complexity (number of fittings, pipes, and references) (N = 10).

| Dep. Variable | Ind. Variable | Constant | Beta | F(1, 8) | R2 | *p* |
|---|---|---|---|---|---|---|
| Visit Count | Fitting Count | 175.33 | 74.97 | 8.45 | 0.51 | 0.020 * |
| | Pipe Count | 160.93 | 48.49 | 10.91 | 0.58 | 0.010 * |
| | Reference Count | 115.39 | 78.30 | 22.99 | 0.74 | 0.001 * |

* Significant at the 0.05 level.

#### 3.1.2. Pipefitter Interaction (Average Visit Duration) by Visual Drawing Complexity (Number of Fittings, Pipes, and References)

A Pearson correlation coefficient was computed to assess the linear relationship between pipefitter interactions (average visit duration) and the drawing complexity metrics (number of fittings, pipes, and references, respectively). The results suggest a weak correlation between pipefitter interactions (average visit duration) and drawing complexity metrics (Table 8). These results indicate that complexity of an assembly drawing does not necessarily indicate that pipefitters will spend more time completing the task when assessed at the 0.05 level.

**Table 8.** Pearson's correlation (r)—pipefitter interaction (average visit duration) by visual drawing complexity (number of fittings, pipes, and references).

| | Pearson's Correlation (r) | *p*-Value |
|---|---|---|
| Fitting Count | 0.153 | 0.673 |
| Pipe Count | 0.346 | 0.976 |
| Reference Count | 0.446 | 0.196 |

### 3.2. Pipefitter Interactions (Visit Metrics) and Search Efficiency

A Pearson correlation coefficient was computed to assess the linear relationship between search efficiency (average convex hull coverage) and the pipefitter interaction metrics (visit count and average visit duration). The results suggest a positive correlation between search efficiency (average convex hull coverage) and average visit duration (Table 9). These results indicate that pipefitters spend more time studying the drawings as the search efficiency (average convex hull coverage) increases. Essentially, pipefitters with a smaller convex hull area are more efficient in finding the required information.

**Table 9.** Pearson's correlation—search efficiency (average convex hull coverage) by pipefitter interaction (visit count, average visit duration).

| | Pearson's Correlation (r) | *p*-Value |
|---|---|---|
| Visit Count | 0.390 | 0.0891 |
| Avg Visit Duration | 0.709 | 0.000 * |

* Significant at the 0.05 level

Linear regression was computed to assess the degree that visit metrics predict search efficiency. Visit metrics were not a good predictor of convex hull coverage when assessed at the 0.05 level (Table 10).

**Table 10.** Regression—search efficiency (average convex hull coverage) by pipefitter interaction (visit count, average visit duration).

| Dep. Variable | Ind. Variable | Constant | Beta | F(1, 18) | R2 | Adj R2 | *p* |
|---|---|---|---|---|---|---|---|
| Search Efficiency | Visit Count | 3.17 | 0.01 | 3.34 | 0.16 | 0.11 | 0.084 |
| | Avg Visit Duration | 2.59 | 0.55 | 3.23 | 0.15 | 0.10 | 0.089 |

### 3.3. Search Efficiency and Performance

A Pearson correlation coefficient was computed to assess the linear relationship between search efficiency (average convex hull coverage) and the performance metrics (assembly time (s), number of errors, and rework (%), respectively). The results suggest a positive correlation between search efficiency (average convex hull coverage) and the pipefitter assembly performance metrics (Table 11). These results indicate that as the search efficiency (average convex hull coverage) increases, pipefitters had a higher likelihood of taking longer to complete the task, making mistakes, and redoing work. In summary, a higher convex hull coverage was found to be a predictor of poor pipefitter performance.

**Table 11.** Pearson's correlation—search efficiency (average convex hull coverage) by pipefitter assembly performance (assembly time (s), number of errors, rework (%)).

| | Pearson's Correlation (r) | *p*-Value |
|---|---|---|
| Assembly Time (s) | 0.589 | 0.006 * |
| Number of Errors | 0.709 | 0.000 * |
| Rework (%) | 0.458 | 0.042 * |

* Significant at the 0.05 level.

Linear regression was computed to assess the degree that search efficiency predicts pipefitter performance. It was found that average convex hull coverage significantly predicted pipefitter performance (Table 12).

**Table 12.** Regression—search efficiency (average convex hull coverage) by pipefitter assembly performance (assembly time (s), number of errors, rework (%)).

| Dep. Variable | Ind. Variable | Constant | Beta | F(1, 18) | R2 | Adj R2 | *p* |
|---|---|---|---|---|---|---|---|
| Assembly Time | Search Efficiency | 378.18 | 459.32 | 9.56 | 0.347 | 0.311 | 0.006 * |
| # Errors | | −2.68 | 0.87 | 18.23 | 0.503 | 0.476 | <0.001 * |
| Rework % | | −2.13 | 2.46 | 4.77 | 0.209 | 0.166 | 0.042 * |

* Significant at the 0.05 level. #—Number of Errors

## 4. Discussion

Survey respondents from a previous study [22] emphasized the need for designers to consult contractors during the design stage. Involving contractors in the design process would influence how the construction drawings are illustrated. Contractors are aware of the craft worker shortage and the high number of contractors retiring. Contractors are tasked with employing and training apprentices meaning they are aware of the nuances craft workers face when reading construction drawings. The involvement of contractors could have decreased the perceived complexity of some drawings by influencing design changes.

This research found that complexity and visit counts are positively correlated. The positive correlation indicates that people visit a visual stimulus more frequently as the visual stimulus complexity increases. These results agree with previous research that complex stimuli require more attention from people to grasp all the pertinent ideas and details of the visual stimuli [9,12,15]. These results indicate that complex drawings are considered unfamiliar or unexpected and do not agree with peoples' "unconscious" [20,21]. However, the results disagree with past findings that claim task completion time increases as visual complexity increases [10,12,18,19]. This disparity is likely because people look at the drawings more often to process information rather than focus on specific fixation points for a longer time. Additionally, complexity was a good predictor of visit counts, as reference count explained 74% of the variability in the model. These results iterate the need to simplify complex or unfamiliar visual stimuli to decrease the cognitive load.

People with lower search efficiency (higher convex hull coverage) require more time to process information. This finding directly relates to past papers that studied spatial cognition [11,12]. People with low spatial cognition have a lower search efficiency. People with low spatial cognition needed more time to process information and visited the drawings more often. People with high spatial cognition have higher search efficiency (better performance) as they can conduct tasks quicker with better accuracy. These results confirm that the presentation of visual stimuli greatly influences peoples' perceptions. Techniques, such as framing, brightness/contrast/saturation, and distance, to highlight the main drawing element [34] will make the drawings more familiar or expected. Familiarity increases the search efficiency of a person. Additionally, these strategies decrease the perceived complexity of visual stimuli.

This research found that people with higher search efficiency (lower convex hull coverage) performed better than people with lower search efficiency (higher convex hull coverage). Additionally, these results indicate that people with higher search efficiency made fewer mistakes, redid less work, and completed the task quicker than people with lower search efficiency. This finding also agrees with past research that people with low spatial cognition have poor task performance [11,12]. Search efficiency was a great predictor of task performance regarding the number of mistakes, assembly time, and rework percentage. The researchers suggest future research to use the same function for search efficiency as it has been proven that convex hulls accurately depict performance [7]. Additionally, when drafters use techniques to improve drawing comprehension and simplify complex designs, construction workers are expected to complete tasks more efficiently and effectively.

## 5. Conclusions

Researchers from various industries have used eye-tracking technology to help them understand how to attract consumers (marketing), direct traffic (wayfinding), recognize hazards (safety), and create a sustainable built environment (architecture). The construction industry is no different. The skills shortage in the construction industry exacerbates the need to make construction drawings more accessible to people with varying degrees of experience. Previous research has extensively studied the influences of different information formats on spatial cognition. This research used eye-tracking technology to analyze information complexity, visit metrics, and search efficiency. Mainly this research differs from previous research by using convex hulls as a search efficiency metric, evaluating the complexity of the drawings for each participant by objective criteria metrics, and evaluating task performance. Search efficiency was studied to understand how people gather information. This research studied how 20 industrial pipefitters interacted with construction drawings of differing complexities, interpreted information, and performed a task. This research found that as a visual stimulus's complexity increases, people interact more frequently with the visual stimulus. Search efficiency also significantly predicts peoples' task performance.

Past research indicated two main methods of making assembly tasks easier to digest, layer-by-layer assembly or block-by-block assembly [35]. These concepts are not new and have been established in the literature. Future research could use eye-tracking to compare the differences between how people view and search for necessary information for task completion between traditional 2D drawings, 2D drawings in a layer-by-layer assembly format, and 2D drawings in a block-by-block assembly format. When creating construction plans or pipe-spool assembly drawings, the drafters are recommended to simulate the building process and draw accordingly. Essentially, drafters are recommended to visualize the building process to make the drawings as streamlined to a real-life application as possible, taking inspiration from design for manufacture and assembly (DfMA) [36].

The authors can see there is a great opportunity for future researchers to dive into the different design possibilities. However, all designs need to account for people with varying expertise, contractor's point of view, and task performance when referencing the drawings.

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## Appendix A

**Table A1.** Pipefitter data [14].

| Pipefitter | Visit Count | Avg Visit Duration | Rework % | Assembly Time | # of Errors | Avg Convex Hull Coverage |
|---|---|---|---|---|---|---|
| Pipefitter 1 | 268 | 3.486 | 19.277 | 2490 | 2 | 0.049 |
| Pipefitter 2 | 359 | 3.743 | 3.061 | 2917 | 2 | 0.045 |
| Pipefitter 3 | 197 | 3.039 | 5.455 | 1634 | 2 | 0.042 |
| Pipefitter 4 | 235 | 3.061 | 0 | 1648 | 0 | 0.04 |
| Pipefitter 5 | 142 | 3.208 | 5.769 | 1565 | 1 | 0.045 |
| Pipefitter 6 | 248 | 2.855 | 10.448 | 2012 | 0 | 0.042 |
| Pipefitter 7 | 325 | 3.205 | 13.514 | 2220 | 2 | 0.043 |
| Pipefitter 8 | 158 | 4.671 | 7.937 | 1892 | 0 | 0.05 |
| Pipefitter 9 | 245 | 2.235 | 10.256 | 2337 | 0 | 0.037 |
| Pipefitter 10 | 335 | 2.844 | 17.347 | 2921 | 4 | 0.06 |
| Pipefitter 11 | 348 | 4.279 | 12.698 | 4314 | 3 | 0.071 |
| Pipefitter 12 | 110 | 2.497 | 2.222 | 1334 | 0 | 0.036 |
| Pipefitter 13 | 312 | 4.508 | 9.483 | 3488 | 2 | 0.06 |
| Pipefitter 14 | 311 | 3.509 | 14.159 | 3371 | 2 | 0.035 |
| Pipefitter 15 | 165 | 4.12 | 3.774 | 1584 | 0 | 0.04 |
| Pipefitter 16 | 163 | 3.839 | 13.83 | 2574 | 2 | 0.048 |
| Pipefitter 17 | 301 | 2.449 | 1.538 | 1942 | 0 | 0.039 |
| Pipefitter 18 | 250 | 4.452 | 8.08 | 2787 | 0 | 0.031 |
| Pipefitter 19 | 357 | 3.473 | 13.158 | 3420 | 2 | 0.051 |
| Pipefitter 20 | 223 | 2.961 | 5.405 | 2217 | 0 | 0.031 |

#—Number of Errors

**Table A2.** Assembly drawing data [14].

| Drawing Number | Total Visit Count | Avg Visit Duration | Fitting Count | Pipe Count | Reference Counts |
|---|---|---|---|---|---|
| 1 | 405 | 3.83 | 5 | 9 | 4 |
| 2 | 573 | 4.78 | 4 | 7 | 4 |
| 3 | 777 | 3.99 | 5 | 9 | 5 |
| 4 | 422 | 3.16 | 3 | 5 | 3 |
| 5 | 528 | 3.16 | 6 | 10 | 5 |
| 6 | 329 | 2.82 | 2 | 3 | 2 |
| 7 | 804 | 3.09 | 8 | 12 | 6 |
| 8 | 563 | 3.46 | 4 | 6 | 3 |
| 9 | 374 | 2.69 | 3 | 5 | 3 |
| 10 | 277 | 2.18 | 4 | 5 | 2 |

## Appendix B

The process for using the two applications in this work was as follows [14]:

1. Collect eye-tracking data using the SMI Eye Tracking Glasses 2.0;
2. Import all eye-tracking data and reference images (assembly drawings) into BeGaze
3. In BeGaze, manually map all recorded fixation points to the appropriate locations on the appropriate reference images;
4. Export eye-tracking event data from BeGaze as a text file and upload to Visual Eyes;
5. Upload all reference images to Visual Eyes and specify the appropriate dimensions of each image;
6. Create a comma-separated value file (.CSV) that lists additional metrics for each pipefitter;
7. A. age, spatial cognition scores, etc.;
8. Upload the comma-separated value file to Visual Eyes

9. Specify a minimum fixation duration and maximum off-stimulus fixations value in Visual Eyes and generate visits;
10. Export file of visit metrics from Visual Eyes, including visit counts, visit durations, and many other statistics.

The visit metrics file exported from Visual Eyes in Step 9 above is a comma-separated value file that includes many visit metrics, as well as the additional metrics that were uploaded in Step 7. This final file was then used for further analysis.

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