The Eye-tracking Study of the Line Charts in Dashboards Design

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Abstract: Dashboards are an important field for an investigation as they are the visual part of the management information systems. Our study aimed to find out the effects of the changes in the types and numbers of line graphs that can be displayed on a single screen simultaneously. Two laboratory experiments were conducted using an eye-tracker to find out how subjects' perception of line graphs on dashboards changes with increase in graph numbers, changes in sizes and increase of the overall area taken up by the graphs on the screen. We show that if the graphs take up the same area, the subjects perceive the line graphs displayed simultaneously in a similar manner. If the subjects are shown an increasing number of graphs of the same size, the subjects take longer to respond to tasks and have higher fixation count per each stimuli. The study revealed that there is no correlation between graph's slope (trend) and subjects' perception.

1 INTRODUCTION

Dashboards (sometimes referred to as instrument panels, control panels) are a tool for data visualisation. Dashboards are a vital part of everyday life, for example for NASDAQ traders (American/Canadian stock exchange traders). One faces a considerable amount of information both during work and during leisure. For working with large amounts of data, especially if managing companies, it is vital to have all the data, trends and correlations 'at the finger tips'. Visualising all the required data on a single computer screen poses a challenge for both programmers and designers.

Providing effective data visualisation is critical to dashboard design. There are many ways of visualising the same information. There are, however, relatively few studies on how the number of graphs displayed at the same time affects the person working with the dashboard. In our study, we will test the effects of the amount of graphs displayed on the screen simultaneously on the subjects' perception of the information. Because the same number of graphs can be displayed on the screen differently, we will also test the effect of the graphs' size on the subjects' perception. This research is important for dashboard design as it presents the basics of any design, which is often neglected during dashboard development. Instead of using scientifically proven methods for designing the dashboards, designers sometimes opt for trial and error method, which is a tedious process that may not yield any results.

With this in mind, it is difficult to address all the challenges that are presented before the dashboard designers. They can be, however, addressed separately. This process of deconstructing dashboards into different design aspects and starting from the more simple ones, would give more solid grounds for further, more complicated work. This approach would also limit the amount of variables that are being studied at one time. In our case, line graphs were studied. After all, they are the most frequently used basic way to visualise a considerable amount of comparable information on websites, user interfaces and dashboards.

This paper aims to start the process of systematic analysis of different aspects of dashboards design. This will give a clearer picture about the perception of information (which contributes to the scientific domain of information perception studies) and help to develop recommendations on better ways of information visualisation not only on dashboards, but also on websites and on other types of user interfaces.

The study was carried out on the effect of the graph sizes and graph count on immediate reactions and answers of the users. Many dashboards are designed and used for quick and easy perception of information. Usually this information requires immediate action. The dashboards also have to visualise a

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considerable amount of information. The tasks given to the subjects during our study were designed to be quick, easy and yielding the quickest responses in order to model a simplified dashboard environment.

2 BACKGROUND RESEARCH

2.1 Information Graphics

Two of the most popular graph types of information graphics (graphs) are line and bar graphs. Line graphs are used to display data or information that changes over time, thus they are used for conveying data trends and distributions. Researchers and designers for a number of reasons often criticize line graphs. Nevertheless, they remain the most popular tool for data visualisation due to their simplicity.

(Cleveland and McGill, 1985) pointed out that "today graphs are a vital part of communication in science and technology, business, education, and the mass media" (p. 530). Even though William Playfair introduced graphs nearly 200 years ago, there remain many questions about their proper use, design and effects on data perception. There are many studies of information graphs (e.g. Tufte, 1983), but a limited amount of scientific data exists on the subject.

Studies had been carried out in order to determine graph perception. A number of researchers addressed the problem of finding the best task- or person-orientated visualisations (Newman and Scholl, 2012).

Small multiples is a term introduced by Edward Tufte in 1983 to describe similar graphs and charts with the same axes and scales that can be compared easily. As Tufte puts it: "for a wide range of problems in data presentation, small multiples are the best design solution." (Tufte, Envisioning Information, 1990, p. 67) It was found that small multiples allow users to compare all different alternatives available to them and to choose the one that interests them (van den Elzen and van Wijk, 2013). This means that the best way to develop a task that consists of finding the right graph among other graphs would be to use small multiples.

Small multiples are often used during dashboard design. Theoretically, however, small multiples have to be placed in a logical order (Tufte, 1983), which is a very hard task, especially if the dashboard is set to display varying information that changes over time.

2.2 Modern Dashboard Design Challenges

Dashboards are visual displays and the information on a dashboard is presented visually, combining text and graphic (Few, 2006). The idea of digital dashboards was devised in the mi ddle of 1970s. When the dashboards gained popularity in 2000s, each company took care of their own dashboards. Development and popularity of the web technology now permits the companies to buy dashboards from third-party companies.

There are several definitions of the word "dashboard". Dashboard is a tool that helps to identify trends, patterns and anomalies for effective decision-making (Brath and Peters, 2004). This tool is intuitive, flexible and easy to use (Harel and Sitko, 2003). Designed for rapid monitoring, dashboards display the most important information on a single screen (Brath and Peters, 2004).

There is a number of recommendations on dashboard design. However, as (Few, 2006) puts it, the process of dashboard design is made too complicated due to the lack of solid design recommendations.

Dundas Data Visualization suggests several characteristics of a good dashboard (2013): "[a dashboard] communicates with clarity; quickly, and compellingly [...] it applies the latest understanding of human visual perception to the visual presentation of information".

There is a question about how many different elements and what amount of vital information can be displayed on the same screen simultaneously. Few suggests that "across the entire dashboard, non-data pixels- any pixels that are not used to display data, excluding a blank background – should be reduced to a reasonable minimum" (Few, 2006) (p 97). This corresponds with Edward Tufte's (1983) 'Data Ink Ratio': "A large share of ink on a graphic should present data-information, the ink changing as the data changes" (p.96).

Following the Data Ink Ratio allows designers to create effective single information graphs. Nevertheless, what is a "reasonable minimum" and how much information can be displayed on the same screen without the user having problems with data perception (Few, 2006). When the data displayed to the subject is greater than subject's working memory a cognitive overload occurs (Mayer, 1989) and the user experiences problems with decision-making and fails to respond adequately to the data.

Completion and accuracy of a task may indicate the degree of graph effectiveness; however, a more in-depth study is required (Goldberg and Helfman, 2010). One of the tools used to understand how the subject perceives graphs is an eye-tracking technology.

There had been a number of discussions on whether graph trends also affect the information perception. This idea is important to consider whilst studying the graph's effects on the subjects. (Newman and Scholl, 2012) tested the above assumption and determined that there are indeed some differences in how rising and declining graphs are perceived by the subjects. The above research indicated that subjects tend to regard the rising graphs in a positive manner, whilst the declining graphs are seen in a highly negative manner. That is to say, the graph trends affect the subjects' perception.

2.3 Eye-tracking

Eye tracking is used to understand the eye movements and gaze positions (Orlov et al., 2014). Based on the eye movements, eye-tracking can be used to determine whether the type of diagram affects how the subject reads it (Goldberg and Helfman, 2010) or whether the subject experiences a cognitive overload whilst working with a distracting dashboard (Bera, 2014).

Two metrics are commonly used in eye tracking: eye fixations and eye saccades (Jacob and Karn, 2003; Duchowski, 2007). The human eye scans the scene by rapid eye movements (called saccades), followed by fixations (relatively stable movements). During saccades, the vision is essentially suppressed.

During fixations, eyes remain almost motionless. A fixation lasts typically for about 200-300 milliseconds (Yarbus, 1965) and is considered to show where viewer's attention is directed (Rayner, 2009). Fixation count is a value revealing the level of cognitive processing of a subject (Bridgeman et al., 1994; Jacob and Karn, 2003). Some studies show that a dashboard with excessive information increases the overall fixation time and count (Bera, 2014).

3 EXPERIMENT 1

3.1 Method

Hypothesis: The number of graphs simultaneously displayed on the screen and their type (rising, declining and stable) affects the process of obtaining visual information. From our hypothesis, we formed 6 research questions:

- RQ 1. Will the number of graphs influence the fixation duration?
- RQ 2. Will the number of graphs influence the task solving time?
- RQ 3. Will the number of graphs influence the number of fixations?
- RQ 4. Will the type of graphs influence the fixation duration?
- RQ 5. Will the type of graphs influence the task solving time?
- RQ 6. Will the type of graphs influence the number of fixations?

Rising, declining and stable line graphs were used (Figure 1) as stimuli. To eliminate the human factor from data generation, a Python script was written to generate graph values procedurally. The values were synthetically generated on purpose, as using real data would have brought certain difficulties and extra variables into our experiments. Even, if a considerable amount of required data were obtained, it would still generate uneven graphs that would not have clear trends. Using specific data would also mean that we would limit the effects of line graphs to a specific domain. All the data used for graph generation did not carry any specific information, such as house prices, or food prices, so that the subjects would pay attention to the trends, rather than what effects those trends would have on them in this specific domain.

According to Cleveland's theory, graphs, displaying slow processes (such as wind speed, water temperature etc.) should follow the banking 45° rule (Cleveland and McGill, 1987). Our graphs were generated in accordance with this rule. The generated values varied, but the difference between sequential values was strictly limited to no bigger than three. The stimuli graphs were even and controlled with no fluctuation.

All the graphs were given the same basic title. The graphs were generated in a way similar to that of (van den Elzen and van Wijk, 2013): the small multiples were generated using the same parameters for all instances except one single variable (van den Elzen and van Wijk, 2013). Small multiples are often used in dashboards. However, they limit the way the graphs have to be displayed: theoretically, small multiples must be placed in a logical order. For our study, we will adopt the small multiple principle, but we will deal with a more complicated scheme. The graphs will be virtually identical but for one variable, but they will have a random order on the screen. Our experiment does not aim to test the benefits of small multiples. Instead, we look at information perception in a simplified dashboard environment.

Yost pointed out a number of different actions subjects can carry out whilst examining information dis-

Figure 2: An example of a 5x5 line graph grid.

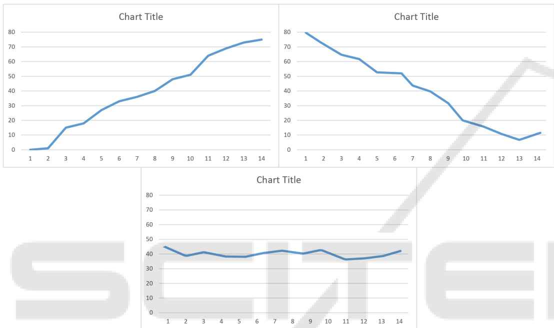

Figure 1: Rising, declining and stable graph visualizations used in the tutorial.

played on the small multiples: identifying, exploring, comparing and even clustering information (Yost and North, 2006). This, however, requires keeping the graphs constant during the entire experiment. However, in order to answer all the research questions listed above, we would have to change two important variables (graphs sizes and active area sizes). For results that are more reliable only one process (a process of identifying a particular graph type) can be introduced.

The graphs were placed side by side forming a grid. The subjects were shown a 2x2, 3x3, 4x4 and, finally graph 5x5 grid for each task. The 5x5 grid was chosen as a reasonable maximum number of graphs (25), see Figure 2.

For each set, the subjects were given a task of finding one type of graph (either rising, declining or stable graph). The process was split into two parts: subjects were first shown line graphs and, once they found the correct answer, they switched to the next screen where the graph grid was copied using grey rectangles. On the second screen, the subjects were told to click on the place, where the correct answer to their task was on the previous screen. This method separated the data about the subjects' fixations and the action of target click.

Before the experiment, all the subjects were shown a tutorial, where they were told what kinds of graphs they would be shown and what task they need to carry out (the task of finding one particular graph type in each set of tasks was explained using images and examples).

After the subjects clicked on their answer on the screen with grey rectangles, an image of an animal was displayed. This powerful semiotic image distracted the subjects. This break introduced a new area of interest, so the subjects would not have to carry out the next task, while focusing on the last.

Before carrying out the experiment, a test experiment was performed in order to check our method against real results and determine any difficulties the subjects may experience during the experiment. For this experiment, the graph grid took up the same area on each screen. The number of graphs for each set of graphs gradually grew (4, 9, 16 and 25 graphs on a single screen). As the number of graphs grew, the graphs became smaller. The subjects were asked to

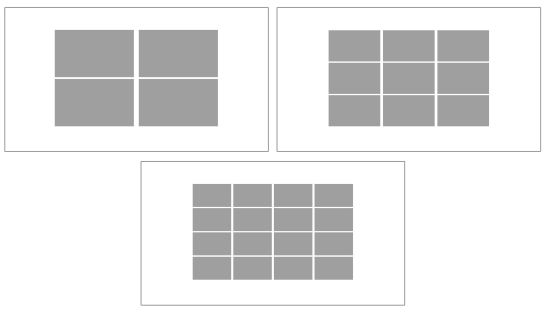

Figure 3: A layout for the 2x2, 3x3 and 4x4 grid for Experiment 1.

find one particular type of graph in each set of graphs (at first they looked for rising graphs, then declining, then stable). After carrying out the test experiment, some minor changes were introduced, such as a more detailed explanation of the tasks in the tutorial.

3.2 Apparatus

The stimulus was presented on a PC with Intel(R) Core(TM) 2 Duo CPU E8400 @ 3.00G Hz, 3.25GB memory and the Microsoft Windows XP operating system. The graphics system consisted of High-performance monitor BENQ XL2411 24" (53cm x 30cm), 1920 x 1080px with 144Hz. Eye movements were registered with an eye tracking system SMI RED250 on a different computer. Fixation detection was done by SMI iViewX software. The eye tracking system was calibrated to the subject's eyes, using five points on a display. The SMI iViewX software saves the coordinates of the points and all the following calculations were done based on the calibration data (Orlov et al., 2014).

3.3 Procedure

37 subjects were given a task of finding a certain type of graph in three sets of graphs. The age of the subjects varied from 18 to 26 years. The subjects were both undergraduate and postgraduate students. We did not perform any vision tests on the subjects. We did however ask the subjects about their eye-sight. All the subjects reported having normal vision or wore lenses/glasses, thus making their vision normal. None of the subjects reported colour-blindness or any other vision defects. All the students were designers/studying design, so any vision defects would have been well known to them and their tutors.

Graphs within the grid were randomized for each subject; as a result, the answer to the task was randomly positioned within the grid. This allowed us to eliminate the effects of the graph positioning on graph perception, as each subject had to look for the correct answer in a randomized point on the screen.

Regardless of the tutorial, the subjects still took time to adjust to the task, so, consequently, they required more time to go through the first set of graphs. To eliminate this delay in our study, we randomized tasks. Unlike the test experiment, rise-decline-stable task sequence was no longer retained and each subject had a different sequence of tasks (i.e. decline-rise-stable, stable-decline-rise etc.).

3.4 Results

In our study, eye movement data was recorded: fixation duration, number of fixations per stimuli and total duration. We also noted whether the answer given by the subject was correct. The task was simple, so none of the subject made any mistakes during the experiment.

The number of graphs simultaneously displayed was determined to have an effect on the fixation durations (Kruskal-Wallis rank sum test (for none normal distributed data, like fixations duration (Duchowski, 2007)): $p - value = .000 < .05; chi - squared = 21.163$). The increase in graph count resulted in a decrease in fixation durations. From Figure 4 we can determine that when subjects looked at four graphs, they had longer fixations, compared to that of the average length of the fixation for 16 graphs.

However, no correlation between the number of graphs displayed on the screen and the number of fixations per stimuli ($p - value = .69 > .05; chi - squared = 1.465$) was found. On average, the subjects made around 10 fixations per stimuli.

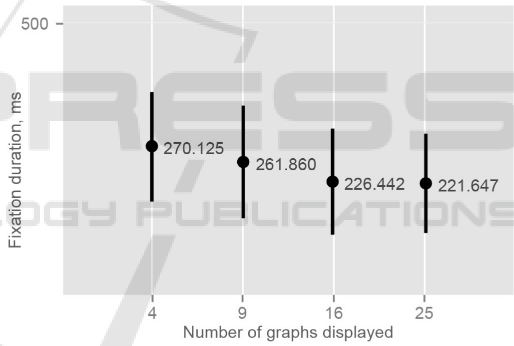

Figure 4: Experiment 1. Total fixation duration.

Surprisingly, the response time (total duration of task solving) is not affected by the number of graphs displayed ($p - value = .44 > .05; chi - squared = 2.702$).

The data was analysed in order to determine whether the type (rising, declining and stable) of graph the subjects were looking for affected the perception of data. The determined that the type of graph does not affect the number of fixations ($F(2, 80) = .65$, $p = .524$) and the overall time for task solving ($F(1, 81) = .932$, $p = .337$) .The Kruskal-Wallis rank sum test determined that the type of graph does not affect the fixation duration ($p - value = .265 > .05; chi - squared = 2.654$). None of these differences was statistically significant.

3.5 Discussion

The first set of questions is aimed to determine the influence of the number of graphs on perception. It was found that this factor influences the fixation duration (RQ1). We can conclude that our findings (see Figure 4) correspond with concepts of attention landscapes by (Velichkovsky, 2006). Longer fixations (with shorter saccades) used for the answering the *What* question corresponds with the time for obtaining the meaning of the visual zone. An opposite happens with shorter fixations (with longer saccades). Shorter fixations are typically used for the searching tasks (the *Where* question) (Burgert et al., 2007). From this we can conclude, that subjects' visual searching strategy switched when the number of graphs reached 16.

No correlation between the number of graphs and the number of fixations (RQ 3) was found. In our research, no influence of graph types was determined (RQ 4, RQ 5 and RQ 6). This result may be explained by the fact that subjects perceive different graph types in a similar manner.

The number of graphs does not influence the task solving duration (RQ2). This might be explained by the fact that the physical size of the graphs was different: the smaller the number of graphs, the bigger size of the each graph. In order to exclude the size factor from the experiment conditions the second experiment was conducted.

4 EXPERIMENT 2

4.1 Procedure

38 undergraduate and postgraduate students took part in the second experiment. In order to eliminate the bias of learning, new subjects were introduced into the experiment. The subjects were from 18 to 28 years of age. The subjects reported about their vision and vision defects. The subjects, who did not have 20/20 vision, were asked to wear their prescribed glasses and lenses. This means that in experiments one and two all the subjects had normal vision without any strong or evident vision defects.

The same Method and Hypothesis was used. We kept the idea of graph randomization and task sequence randomization. The basic set up of the experiment was the same as for the first experiment. This time, however, we took a different approach to how the graphs were displayed on the screen. Unlike the previous experiment, the size of the graphs remained constant (256x153 px), consequently the area taken up the graphs on the screen changed noticeably (from 512x306 px for the 2x2 grid up to 1280x765 px for the 5x5 grid), see Figure 5.

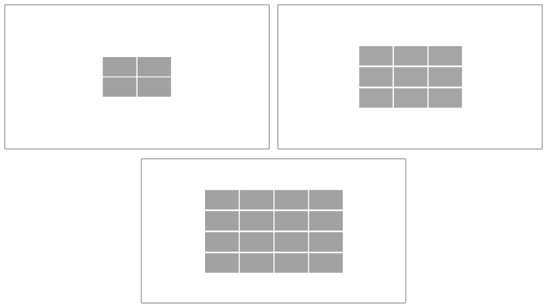

Figure 5: A layout for the 2x2, 3x3 and 4x4 grid for Experiment 2.

4.2 Results

We found that the number of graphs affects the number of fixations (ANOVA: F(1, 774) = 126.38, p = .000). Figure 6 (left) provides the mean of the fixation numbers. Generally, a smaller number of graphs had a smaller number of fixations.

Further analysis showed that the time required for task completion is also influenced by the number of graphs (ANOVA: F(1, 94) = 11.024, p = .001). Figure 6 (right) shows the positive correlation between the number of graphs and the total task solving time.

We did not determine the effect of the number of graphs on the fixation duration (The Kruskal-Wallis rank sum test: $p-value = .07 > .05; chi-squared = 7.047$).

The overall fixation duration, however, almost doubled during the second experiment, going from the mean of 13.317 for the 2x2 grid to 21.72 for the 5x5 grid.

It was determined that there was no correlation between the types of graphs the subjects were tasked to find on the screen and fixation duration (The Kruskal-Wallis rank sum test: $p-value = .829 > .05; chi-squared = 0.375$), fixation count (ANOVA: F(2, 93) = .419, p = .659) and time for task completion (ANOVA: F(2, 93) = .635, p = .532).

4.3 Discussion

This experiment was designed in order to determine the importance of the graph count and type in dashboard design. We found that the number of graphs influences the number of fixations. The number of graphs (RQ 2, RQ 3) also influences the total task solving time. The number of graphs (RQ 1) does not affect the fixation durations.

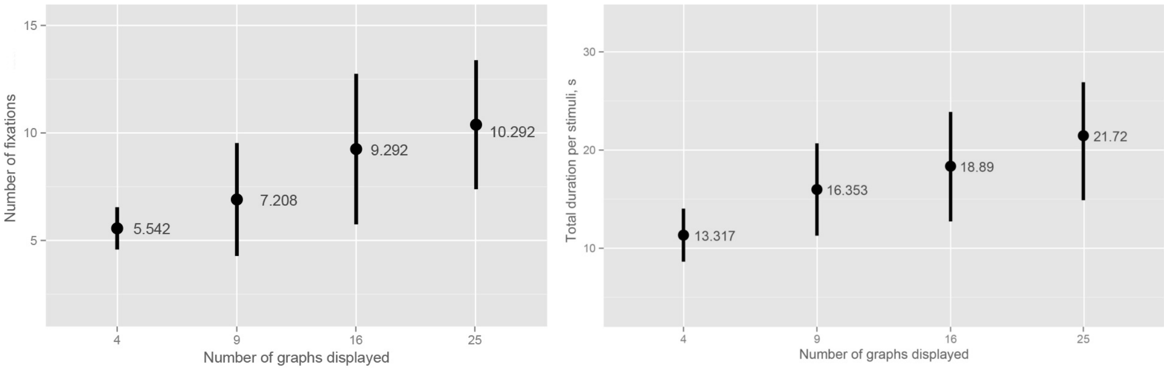

Figure 6: Experiment 2. Left: Number of fixations per each graph grid type. Right: Total time required for the subjects to respond to the task.

When compared to the Experiment 1, we can conclude that the fixation durations are affected greatly by the graph sizes. There are several possible explanations for this result. It could be because when a greater amount of details was available to the subjects, subjects spent more time studying the details on the graph rather than solving the task. This could also be explained by considering that, during perception, each graph's importance and the amount of information it displays for the user depends heavily on the area it occupies on the screen.

Unlike the first experiment with no significant change in fixation count, during the second experiment mean fixation count almost doubled from 5.542 fixations per 2x2 stimuli to 10.292 fixation for 5x5 stimuli during the second experiment.

The second group of research questions focuses on the graph's type. As in an Experiment 1, here we also did not find any influences of this factor on the fixation duration, task solving time and the number of fixations (RQ 4, RQ 5, and RQ 6).

5 GENERAL DISCUSSION

The results display an evident difference between the effects of the two possible approaches to line graph distributions on the screen.

Subjects studied bigger graphs with longer fixations. When working with a graph that takes up a relatively big area on the screen, the subjects studied it in more detail. For the smaller graphs, the subjects opted for a 'glancing over'. In the first experiment, the subjects perceived a graph grid of four line graphs and a grid of 25 graphs with the same speed. In the second experiment, when the graphs were all of the same size, four graphs were perceived faster than 25. This means that the useful area of the screen (not the graph count) correlates to the time required to solve the task. During dashboard design, the designers should consider this finding: the size of the graph depends heavily on the level of detail that is needed for a specific task. The information for immediate reaction and quick overall assessment should be displayed on a small area relative to the screen.

Our study shows that if four graphs are being displayed, their total size is recommended to be 16% of the total active screen and 36% of the screen for 9 graphs. Graphs that convey a more in-depth information have to be larger, as larger graphs are always studied in more detail.

It is not necessary to fill the screen with large graphs. Designers have to sacrifice the useful screen area in order to increase the speed of problem solving and information assessment. Nevertheless, it is important that the rest of the available space must remain empty, as adding images and other graphics to the dashboard results in so called "distracting dashboard" (Bera, 2014).

It was determined that the graph type does not affect the subjects' perception. There is no evidence showing that the subjects perceive more 'positive' rising graphs better than the declining graphs, or find stable graphs more readily. This remains true for both experiment setups. (Goldberg and Helfman, 2010) determined that line graphs do not promote left to right scanning of the graph's body, instead the subjects opt for a 'back and forth' approach. This behaviour supports our results: if the subject studies the graph using a back and forth eye movement, there should be no actual preference to which graph types the subject finds faster. If the graphs were to be scanned from left to right, declining graphs would have been easier to detect, as their lines start at the upper left corner of the axis.

On the other hand, the study by (Newman and Scholl, 2012) shows that the rising and declining graphs, in his case bar graphs, are still perceived in a different manner: rising graphs are seen by the subjects to be more optimistic than they really are, while the subjects interpret a declining graph in a negative manner. As our subjects were not questioned on whether they found it easier to find a certain graph type, we cannot conclude whether the graph types have absolutely no effect on users in terms of positive or negative perception and correct decision-making.

6 CONCLUSION

Our findings can be applied to a whole number of different domains e.g. web design. While not being classic dashboards, web pages, as well as other user interfaces, often carry out the same tasks as dashboards (display information graphs, allow users to make immediate decisions, convey important information). The paper could be used as one of the guidelines for both web and dashboard designers, when making choices about graph placements and graph sizes relative to the screen. Many websites could benefit from the idea that the amount of graphs that is being displayed simultaneously is not as important as the size of those graphs (or any other images, text-blocks or information).

When designing the dashboard (or a dashboard screen) designers should note that the graphs that occupy a relatively small amount of the active screen convey information quicker than larger ones.

It also important to note that during the first experiment a change in a visual searching strategy by the subjects was noted. This is an interesting concept that can be explored further in future works.

The paper deals with the idea of whether bigger graphs are better for perception speed and whether a greater number of graphs makes information perception difficult. Our findings showed that the useful screen area corresponds to the speed of the problem solving. This means that dashboard designers should sacrifice screen area, use smaller graphs and leave empty spaces if the dashboard (dashboard screen they are designing) is used for basic immediate assessment. If a more in-depth assessment is required, larger graphs are recommended.

The paper also contributes to the studies of information perception in terms of both user interfaces and infographics. The paper may serve as the base for a more in-depth study of information perception. As a follow-up of the experiments, an eye-tracking study should be carried out on other types of graphs, such as bar graphs or pie charts, in order to find out whether our conclusions are true for other types of information graphs. Adding graphs that are more complicated or information from a specific domain, greater distracting points of interest or longer and more demanding tasks (such as exploring, concluding, comparing and clustering (Yost and North, 2006)) could also be introduced. This would help to understand how designers should act, when their dashboard needs to convey more information (not just help to identify a graph with the correct trend relative to the task) or when only brief and immediate information needs to be displayed.

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