THE IMPACT OF COGNITIVE FACTORS ON DATA VISUALIZATIONS

D11

IDEALVis Consortium

http://idealvis.inspirecenter.org/

European Union
European Regional Development Fund

Republic of Cyprus

Structural Funds
of the European Union in Cyprus

ΙΔΡΥΜΑ
ΕΡΕΥΝΑΣ ΚΑΙ
ΚΑΙΝΟΤΟΜΙΑΣ

Executive Summary

This deliverable's purpose is to provide a detailed report regarding the analysis and results of data that was obtained through the experiments that took place as part of Tasks 4.1 and 4.3. Specifically, the main objective of the deliverable is to provide insight on the effect and influence that different human factors have on how users process and understand data. The data analysis processes which produced the outcomes described in this report utilized data captured from the two first user studies performed in the project.

Initially, during the User Profiling Study the team collected the participants' key intrinsic human factors, including their level of expertise in the data analytics domain, as those factors can influence a person's visual information processing. In the second user study participants were exposed to various visual analysis tasks generated from realistic sales datasets. Those tasks varied in terms of visualization type, complexity level and alterations/enhancements (alteration here refers to an element/visual intervention that is added on the original data visualization as means of enhancing or personalizing the user's information processing process). The participants' performance and accuracy were captured while they navigated over: (i) the original non-altered content, which included data visualizations without any alterations or enhancements (control condition), and (ii) the altered content, which included altered/enhanced data visualizations (experimental condition).

This deliverable reports the findings of the above studies, analyzing the main effects (in terms of user performance) of several human factors on different data visualization types and visual interventions (i.e., enhancements/altered visual elements). Some of the findings presented in this work include (i) the prominence of the column chart as being the most performant data visualisation for lower complexity tasks across all human factors, how other data visualizations become important for more complex analysis tasks and how this is affected by human factors; (ii) how changing the proximity or size of prominent data visualisation elements benefits performance mostly in higher complexity tasks; (iii) how data visualization grid lines are a necessary visual element across all task complexity levels and human factors; (iv) how data labels provide a performance benefit to the user mostly in lower complexity tasks and how this is affected by human factors in higher complexity tasks; (v) how the data visualization dark theme is best for performance when used in low complexity tasks and how higher expertise users can also benefit by this theme in higher complexity tasks; (vi) the importance of sorted data regarding performance, across all tasks and especially tasks of higher complexity; and finally (vii) the higher positive effect of duller color palettes in terms of user performance across human factors.

Table of Contents

List of Figures

List of Tables

1 Introduction

The goal of this deliverable is to demonstrate the overall process used for identifying the impact of cognitive factors on data visualizations based on the outcomes of the project's studies.

Section 2 of the deliverable describes the main human factors that form the majority of the user model. Those human factors are described on a theoretical level, while also related literature as to the factors' impact on data visualizations is presented, strengthening the justification of their selection. Additionally, the last part of this section demonstrates the formalised data analysis procedure used to classify/segment our participants for each human factor in different levels. Next, Section 3 of the deliverable presents the design of User Study 2 (i.e., Data Visualization Study). In this study, 60 participants engage with various visual analysis tasks of varying complexity, with each task constructed using different visualization conditions to capture the performance and accuracy of all participants as it is exhibited on this set of conditions. In Section 4 we demonstrate the major analysis steps performed using the human factor user classifications described in Section 2, and the performance and accuracy data collected as a result of the user study described in Section 3. Moreover, in Section 4 we introduce and discuss the findings of the analysis i.e., the impact of human factors on data visualizations. The results of impact are presented in terms of (i) impact on the visualization type and (ii) impact on different visualization elements (i.e., enhancements/altered visual elements).

2 Human-centred User Model Factors

This section aims to identify and introduce the key human factors that were explored in Task 4.1 and were found to influence the user's performance and accuracy in information processing. Initially, the definition of each human factor is provided to the reader while the effect posed by each factor in information processing becomes apparent by mentioning related previous research works. With the theoretical aspects in place, we also present the formalised data analysis procedure or scale, used to analyse the results of our 60 participants for each human factor. The analysis of a human factor has the ultimate purpose of classifying users in different levels for that factor. The formalised analysis and classification mechanisms described in the next subsections make up integral parts of the user modelling process, and therefore some of this content is also part of deliverable D12:The Human-centred User Model for Adaptive Data Visualizations. Following our main findings regarding research on individual differences in the data visualization and exploration field, we focus on the following categories of human factors: cognitive abilities, cognitive styles, and expertise.

2.1 Cognitive Abilities

Cognitive ability can be defined as *a mental capability that involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly, and learn from experience* (Gottfredson, 1997). Common cognitive abilities explored in visualization research include Perceptual Speed, Visual Working Memory, Verbal Working Memory, Spatial Ability, Spatial Memory, and Associative Memory. In our work we explore some of the most influential factors including **Visual Working Memory**, **Speed of Processing,** and **Control of Attention** (with the latter two being closely related to Perceptual Speed).

2.1.1 PERCEPTUAL SPEED

This cognitive ability is defined in literature as *Speed in comparing figures or symbols, scanning to find figures or symbols, or carrying out other very simple tasks involving visual perception* (Ekstrom, et al., 1976). (Toker, et al., 2012) investigated the effect of a user's Perceptual Speed on the effectiveness of bar and radar graphs. Findings suggest that Perceptual Speed affected completion times i.e., performance in both graphs since high Perceptual Speed participants completed tasks faster. Another study that proves the significance of Perceptual Speed is the work of (Lallé, et al., 2017) which reports that users with lower levels of Perceptual Speed find it harder to compare visualizations. The study further suggests that such users might benefit from adaptations that remind them to perform comparisons when data values change rarely. (Toker, et al., 2013) further investigated how Perceptual Speed influences a user's gaze behavior and found that high Perceptual Speed participants had higher fixation (maintaining gaze at one point on the stimuli) rates and lower fixation duration while low Perceptual Speed participants spent more time in the legend with more frequent transitions to it. Very similar results are discussed in by (Steichen, et al., 2013). This suggests that lower Perceptual Speed users might benefit from an adaptation related to the legend of the graph. Moreover, the study concludes that low Perceptual Speed participants are affected more by different ways of visualizing data. Adaptive support for visualizations (highlighting interventions) was explored by (Carenini, et al., 2014) which concluded that users with low to medium cognitive measures (including Perceptual Speed, Visual and Verbal Working Memory) will benefit from adaptive interventions.

2.1.2 VISUAL WORKING MEMORY

This cognitive ability is essentially a system that stores visual information between eye fixations, in the form of integrated objects which can contain colors, orientation and shape. Several studies discussed in the Perceptual Speed section also investigated the effect of Visual Working Memory in the context of visualizations. (Toker, et al., 2012) reported that high Visual Working Memory participants had a higher preference for radar graphs over bar graphs. Here we can see how Visual Working Memory can influence the subjective preference and ease-of-use for visualization types. Another similar finding from (Lallé, et al., 2017) showed that participants with high Visual Working Memory tended to prefer a deviation chart over a map. In trying to predict the user's cognitive abilities and visualization task though eye gaze data (Steichen, et al., 2013) found that high Visual Working Memory participants had lower time until they performed their first fixation. Additionally, in the study of (Carenini, et al., 2014) participants with low or average Visual Working Memory rated a visual intervention (Average Reference Lines) lower than participants with higher Visual Working Memory. This effect was explained as a visual destructor since this type of intervention poses a line on multiple bars.

2.2 Cognitive Styles

The term cognitive style was introduced by (Allport, 1937) and has been described as a person's typical or habitual mode of problem solving, thinking, perceiving, and remembering. (Riding & Cheema, 1991) has analyzed and grouped multiple cognitive styles into two principal or *style dimensions*, the Wholist-Analyst and Verbalizer-Imager.

2.2.1 FIELD-DEPENDENT INDEPENDENT

The Wholist-Analyst style dimension has multiple terms that define it, one of the principal terms is **Field-Dependence Independence** (FD-I) (Riding & Cheema, 1991). The FDI term has been proven not to be an intellectual style, but instead a construct that represents an individual's ability in separating information from its contextual surroundings. A field independent (FI) individual has less difficulty in separating information from its surroundings, while a field dependent (FD) individual will be more likely affected by external visual cues (Zhang, 2004). In visualization research (Steichen, et al., 2020) proved that while the user is interacting with a typical visual information task using a bar graph or a line graph it's feasible to infer the user's cognitive style (FD-I) using eye tracking mechanisms. The results further demonstrated that FD participants have less structured eye movements while being more able to shift focus on important aspects of the graph. In another study (Steichen & Fu, 2019) explored how FI and FD users differ on how they enable different visual aids. Results indicated that FD participants utilized the visual aids more than FI participants which suggests that such users may benefit from an interface that includes visual aids (manually or adaptively). Moreover, FD participants made significant use of the "show data aid" (overlays data values on visualization), denoting that such users may prefer a visualization that also contains some "supportive" textual aspects.

2.3 Domain Expertise

A factor that varies between individuals and poses an important steppingstone in making sense of a visualization, is prior expertise with a given visualization but most importantly the overall expertise in the field of business data analytics. Expertise cannot only affect a user's performance, it can also affect the visualization effectiveness as the search task gets more complicated (Bryce, 2000). For measuring the expertise of our participants in the context of IDEALVis we utilized the **Perceived Expertise Tool** (PET) (Germanakos, et al., 2021) which is one research outputs of this project.

2.4 Factor's Formalised Data Analysis Procedure

The formalised analysis procedures illustrated in the following sub-sections are part of the analysis notebooks in APPENDIX 1 under the *psy_tests* and *questionnaires/business_role.html* folder/files.

2.4.1 COGNITIVE CHARACTERISTICS

Assume that a user u_i performs a task ts_j that belongs to a given cognitive ability / cognitive style test cs. The system captures the user's response and stores it as a quintuplet represented as $ts_j^{cs}(u_i) = (cs, j, u_i, val, t)$, where cs represents the cognitive test, j represents the task's number, u^i represents the user, val represents the correctness of the provided response ($true$ or $false$), and t represents the time in milliseconds taken by the user to provide the response. In the context of IDEALVis cs can be s (i.e., Speed of Processing), c (i.e., Control of Attention), vwm (i.e., Visual Working Memory) or fdi (i.e., Field-Dependent, -Independent).

The set of all tasks answered correctly by the user u^i for a specific cognitive test cs is denoted as:

$$T^{cs}(u_i) = \{ts_j^{cs}(u_i): ts.val = true, \forall\, j\}$$

The number of tasks answered correctly by the user u^i for a specific cognitive test cs is defined as:

$$cr^{cs}(u_i) = |T^{cs}(u_i)|$$

The average response time for a cognitive test cs for a user u_i is defined as:

$$rt^{cs}(u_i) = \frac{\sum_{\forall ts_j^{cs}(u_i) \in T^{cs}(u_i)} ts_j^{cs}.t}{cr^{cs}(u_i)}$$

The average response time for a cognitive test cs for all users is defined as:

$$RT^{cs} = \frac{\sum_{\forall u_i} rt^{cs}(u_i)}{|\{u_i: rt^{cs}(u_i) > 0\}|}$$

The deviation of the average response times for a cognitive test cs (applicable only to s and c) for all users is defined as:

$$dv^{cs} = \frac{RT^{cs} \times 10}{100}$$

The upward deviation of average response times for a cognitive test cs (applicable only to s and c) for all users is defined as:

$$dvu^{cs} = RT^{cs} + dv^{cs}$$

The downward deviation of average response times for a cognitive test cs (applicable only to s and c) for all users is defined as:

$$dvd^{cs} = RT^{cs} - dv^{cs}$$

Speed of Processing and Control of Attention: Cognitive test s measures the speed of processing level of a user. A user u_i is either classified as having a high level of processing speed, assuming an average response time $rt^s(u_i)$ lower than dvd^s; classified as having a low level of processing speed, assuming an average response time $rt^s(u_i)$ higher than or equal to dvu^s; or classified as having a medium level of processing speed, assuming an average response time $rt^s(u_i)$ that falls between dvu^s and dvd^s. Similarly, cognitive test c measures the control of attention level of a user. A user u_i is either classified as having a high level of attention control, assuming an average response time $rt^c(u_i)$ lower than dvd^c; classified as having a low level of attention control, assuming an average response $rt^c(u_i)$ higher than or equal to dvu^c; or classified as having a medium level of attention control, assuming an average response of $rt^c(u_i)$ that falls between dvu^c and dvd^c.

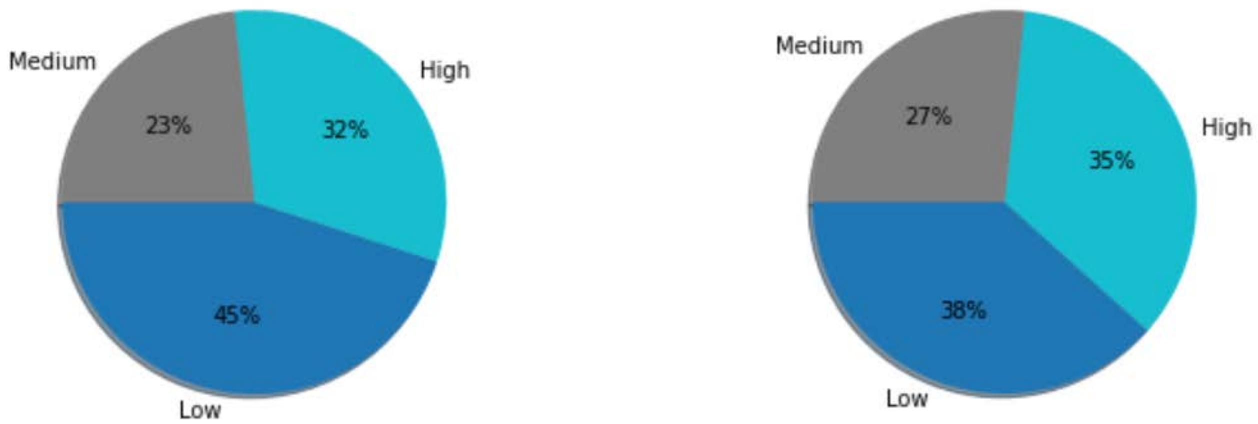

Figure 1 - Speed of Processing (Left) and Control of Attention (Right) Groups (N=60)

Visual Working Memory: Cognitive test vwm measures the visual working memory of a user. This cognitive test consists of 21 tasks ts which are broken down to 7 levels (3 questions per level). Each time the user answers three questions correctly their working memory level raises by 1. When the user makes a mistake, the test is ended, and their working memory level is the current level when they answered wrong.

The level of a user u_i for cognitive test vwm is defined as:

$$vwml = \frac{cr^{vwm}(u^i)}{21}$$

Moreover, a user is classified as having a low visual working memory if they have a $vwml$ of 1 or 2, medium visual working memory if they have a $vwml$ of 3, 4 or 5 and a high visual working memory if they have a $vwml$ of 6 or 7. For the purpose of this analysis and according to our sample, we classified users into two groups (i.e., High and Low). A user is considered to have high visual working memory if they have a $vwml$ of 5 or above, or low visual working memory if they have a $vwml$ of 4 or below.

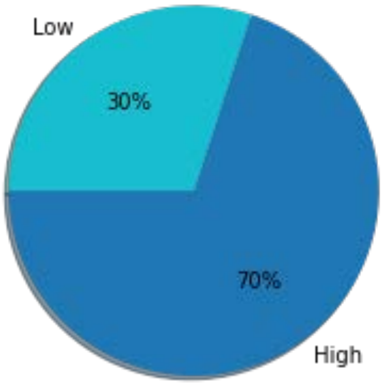

Figure 2 - Visual Working Memory Groups (N=60)

Field-Dependent Independent: Cognitive Style Test fdi consists of 18 tasks ts that user u_i must complete. The final score of a user u_i is denoted as $cr^{fdi}(u_i)$ and the level of the user (i.e., field-dependent, -independent, or intermediate) is calculated with two percentile values derived from the set of all users' scores $\{cr^{fdi}(u_i), \forall i\}$.

For the fdi cognitive test, the 50th and 75th percentiles of all users' scores are defined below respectively as $Plow$ and $Pmid$.

$$Plow = \left\lceil \frac{50}{100} \times \left|\{cr^{fdi}(u_i), \forall i\}\right| \right\rceil$$

$$Pmid = \left\lceil \frac{75}{100} \times \left|\{cr^{fdi}(u_i), \forall i\}\right| \right\rceil$$

Accordingly, a user is classified as being field-dependent if they have an fdi score less than $Plow$, field-independent if they have a score higher or equal to $Pmid$, and intermediate if they have a score higher than or equal to $Plow$ and lower than $Pmid$. For the purpose of this analysis and according to our sample, we classified users into two groups instead (i.e., field-dependent, and field-independent). A user is classified as field-dependent (FD) if they achieve a final score of $cr^{fdi}(u_i)$ equal to 8 or lower. Moreover, to be classified as field-independent (FI) a user must achieve a final score of $cr^{fdi}(u_i)$ equal to 9 or higher.

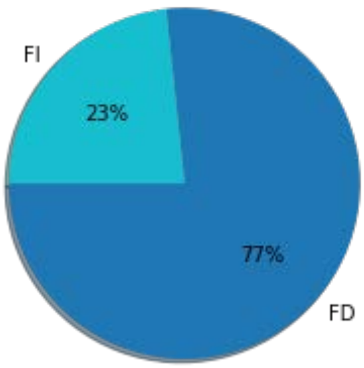

Figure 3 - FDI Groups (N=60)

2.4.2 PERCEIVED EXPERTISE FACTOR (LIKERT SCALE)

Assume that a user u_i answers a Likert-scale question q_j that belongs to a questionnaire lq. The system captures the user's answer and stores it as a quadruplet represented as $q_j^{lq} = (lq, j, u_i, val)$, where lq represents the questionnaire, j represents the question's number, u^i represents the user, and val represents user's response in a numerical format (maximum and minimum values of this variable are defined by the underlying questionnaire scale). In the context of this analysis lq is pet (i.e., Perceived Data Analysis Expertise Tool).

The responses for a given Likert-scale questionnaire lq provided by user $u_i$are defined as:

$$Q^{lq}(u_i) = \{q_j^{lq}(u_i), \forall\, j\}$$

The sum of all responses for a given Likert-scale questionnaire lg provided by user u_i is defined as:

$$qs^{lq}(u_i) = \sum_{j \in Q^{lq}(u_i)} j.val$$

Perceived Expertise: pet is a 10-item questionnaire that is used for measuring the perceived expertise of individuals in the data analytics domain. The total score a user u_i can acquire from this test is 50. The final score of a user u_i is denoted as $qs^{pet}(u_i)$ and the level of the user (i.e., low, high, or medium expertise) is calculated with three percentile values derived from the set of all users' scores $\{qs^{pet}(u_i), \forall i\}$.

For the pet questionnaire, the 25th, 50th and 75th percentiles of all users' scores are defined below respectively as $Plow$, $Pmid$ and $Phigh$:

$$Plow = \left\lceil \frac{25}{100} \times |\{qs^{pet}(u_i), \forall i\}| \right\rceil$$

$$Pmid = \left\lceil \frac{50}{100} \times |\{qs^{pet}(u_i), \forall i\}| \right\rceil$$

$$Phigh = \left\lceil \frac{75}{100} \times |\{qs^{pet}(u_i), \forall i\}| \right\rceil$$

Accordingly, a user is classified as having a low level of expertise in the data analytics domain if they have a pet score less than $Plow$, medium level of expertise if they have a score higher or equal to $Pmid$ and lower than $Phigh$, and high level of expertise if they have a score higher than or equal to $Phigh$. For the purpose of this analysis and according to our sample, we instead used three threshold score values to define which users are to be classified as having a low, medium, or high expertise level. Moreover, a user is classified as having a low expertise level if their total score $qs^{pet}(u_i)$ is 35 or lower, classified as having a medium expertise level if their total score $qs^{pet}(u_i)$ is between 36 and 40, and finally classified as having a high expertise level if their total score $qs^{pet}(u_i)$ is between 41 and 50 (inclusive).

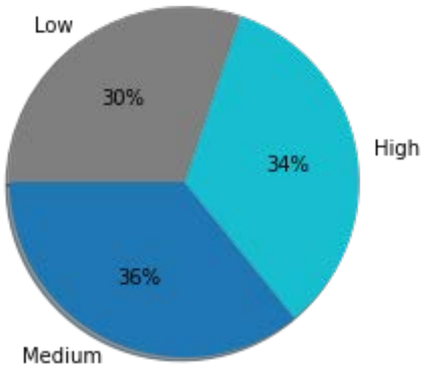

Figure 4 - Perceived Expertise Groups (N=53)

3 Data Visualization Study Design

For understanding how users with different individual differences perform when solving data visualisation tasks, we designed this user study where participants had to engage with various visual analysis tasks of varying complexity, with each task constructed using different visualization conditions. Moreover, the user study's purpose is to capture the performance and accuracy of all participants as it is exhibited on this set of varying conditions. The intuition behind this study is that participants who differ significantly in terms of individual differences / human factors, should also exhibit different performance and accuracy when solving visual analysis tasks. We expect that this differentiation in performance amongst different participants should also be influenced by different visualization types, but also by different visual elements i.e., visual alterations.

3.1 Study Materials

3.1.1 THE SYSTEM

Prior to running this study our team initiated the second phase of development, which developed the IDEALVis visualization engine. The experience from building the user model in combination with the visualization engine provided the ability to create visualization task experiments where each experiment contained a set of tasks that the participant must complete. Specifically, a visualization task experiment is defined by a set of visual analysis tasks that are loaded one after the other once the participant provides a response. At each task the participant can view the analysis task question or narrative that specifies what the participant is looking for. Right below the narrative, the participant can see the data visualization that is fixed and not interactive. Finally, a list of multiple-choice controls enables the participant to respond and submit their answer. Throughout the procedure, the system is capturing for each task the time it took for the participant to respond (in milliseconds) and whether the response of the participant was valid or not. A visual analysis task example can be seen in Figure 5.

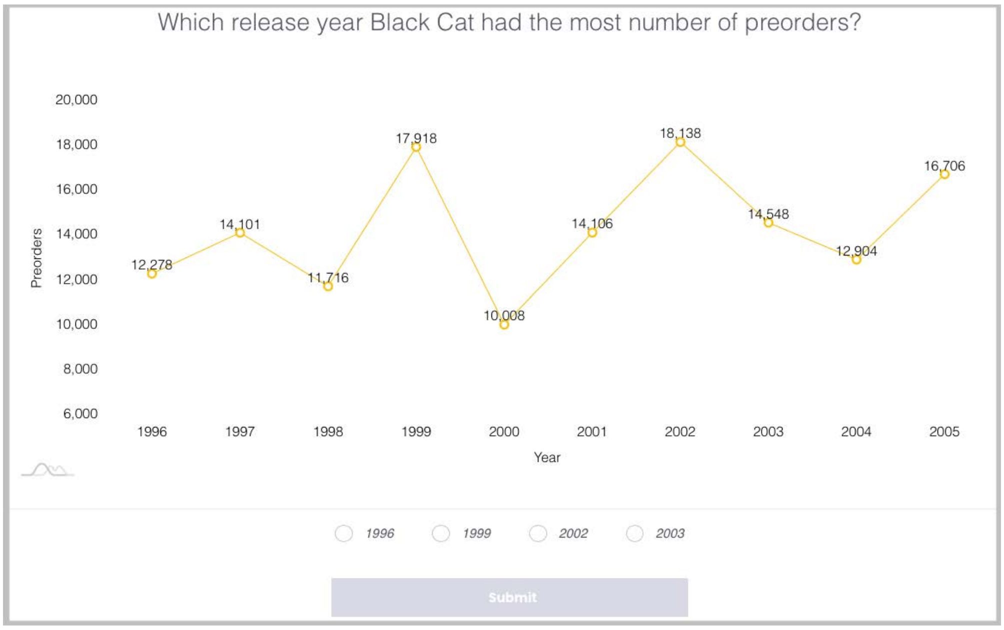

Figure 5 - Example Visual Analysis Task

3.1.2 DATA VISUALIZATION TYPES

One of the important decisions we had to take when designing this user study, was the type of data visualizations that we would include in the various analysis tasks. According to previous findings (Amyrotos, et al., 2021) that emerged from the IDEALVis project we decided to use the following data visualizations for this user study: Bar Charts, Column Charts, Line Charts, Radar Graphs, Pie Charts and Data Tables. Basically, those data visualization types were selected because they are some of the most utilised data visualizations in the business domain. While the Radar Graph is less widely used in the domain of interest when compared to the rest of the selected charts, we decided to include it since participants with higher visual working memory may have higher preference for this type of chart over bar charts (Toker, et al., 2012).

3.1.3 STUDY DATASET

To cater for the diverse user analysts' cohort participating in the project and the nature of their expertise, we opted for the construction of a synthetic dataset, with concepts that are easy for comprehension and analysis. More specifically, a synthetic dataset of comic book sales was constructed, with typical dimensions, such as time, product characteristics and location characteristics, and a few distributive (e.g., quantity, price) and algebraic measures (e.g., average price, weighted price).

3.1.4 THE ANALYSIS TASKS

Using the generated comic book sales dataset, we produced 160 visual exploration tasks. The types (i.e., taxonomy) of visual analysis tasks we used are low-level analysis tasks that largely capture people's activities while employing information visualization tools (Amar, et al., 2005). Moreover, the 160 visualization tasks were created in 4 distinct experiments, the Chart Type Experiment, the Task Complexity Experiment, the Dimensionality Experiment, and the Visual Elements Experiment.

Chart Type Experiment: This experiment is composed of simple comparison tasks across all visualization types.

Task Complexity Experiment: This experiment introduces some more complex tasks such as detecting data anomalies, computing derived values, or retrieving values.

Dimensionality Experiment: While the tasks in Chart Type and Task Complexity Experiments are using a single data dimension (i.e., single chart series / single table attribute) the Dimensionality experiment introduces 2-, 3- and 4-dimensional tasks, while it also includes the correlation task type.

Visual Elements Experiment: Tasks in the above experiments act as control tasks to this experiment, since data visualizations in previous experiments are all delivered using a default visual setting i.e., no alterations on visual elements. Moreover, this experiment has analysis tasks inspired from a mixture of tasks taken from the control experiments. Analysis tasks for the Visual Elements Experiment are spitted in 8 sets and each of those sets introduces a unique experimental condition. The experimental condition of each set is essentially a visual element alteration. The different experimental visual element conditions and how those were applied on different data visualizations is further described in Table 2. Moreover, in Figure 6 we illustrate the 8 different elements as they are applied on some of the visualization types.

In Table 1 we provide more information regarding each of the 4 analysis task experiments. The table includes information regarding the analysis task types that were used in each experiment and states the types of data visualizations that were used for each of those tasks.

3.1.5 ANALYSIS TASK COMPLEXITY

Another important aspect that we had to control was the complexity levels of each of the tasks. Complexity is an important factor that we wanted to explore with regards to the impact of human factors on different data visualization types and different visual elements, and therefore each of the 160 tasks were assigned one of three complexity levels: Low, Medium, High. More specifically, the complexity of a task is a factor that was controlled by (i) the data dimensions used for creating the data visualization and (ii) by the underlying task type that the participant had to perform for the given visual analysis task (e.g., Simple Comparison). Next we provide information as to what each complexity level means in the context of our analysis tasks.

Low Complexity Tasks: This level of complexity denotes simple comparison tasks where the visualization always illustrates a single data dimension. These comparison tasks usually ask the participant to spot on the data visualization a specific case e.g., the highest value. An example task's narrative is the following "*Which comic book title has the lowest number of units sold?*".

Medium Complexity Tasks: This level of complexity denotes tasks where the visualization may illustrate one or two data dimensions. Moreover, tasks assigned in this complexity level can be (i) simple comparison tasks with 2 data dimensions as opposed to low complexity tasks, (ii) detect anomaly tasks (e.g., *Which period of sales presents a significant increase in unit sales?*), (iii) retrieve value tasks (e.g., *Which comic book has the second highest sales?*) and compute derived value tasks, where the participant is required to perform a calculation (e.g., *What is the total number of months (count) that sales were between 6500 and 7000?*). The latter three types of tasks always use a single data dimension in this complexity level.

High Complexity Tasks: This level of complexity denotes tasks where the visualization may illustrate from one and up to four data dimensions. Tasks assigned to this complexity level can be simple comparison tasks of two, three or four data dimensions. Simple comparison tasks with two data dimensions are more complex than those found in medium complexity tasks (e.g., *Which month had the highest deviation between minimum and maximum price for the sales of Superman in comic bookstores?*). Next, this complexity level also has "detect anomaly" tasks with a single data dimension but those are more complex than those found in medium complexity tasks (e.g., *Decide which one of the following comic categories has a value of sales that does not belong in any group*). Moreover, this complexity level has "compute derived value" tasks which might have one and up to four data dimensions (e.g., *What is the difference in popularity between the two highest selling comics?*), with those of a single dimension being more complex compared to those found in the medium complexity tasks. Finally, this complexity level introduces the correlation tasks which can have three or four data dimensions. An example of a correlation task is "*Which comic book title demonstrated a decrease in sales between 2018 and 2020?*" where in this case 2018, 2019 and 2020 are three separate data dimensions.

Table 1- Visualization Type per Task Type for Each Analysis Tasks Experiment

Experiment	Task Type	Bar	Column	Line	Radar	Pie	Table	Total Tasks
Chart Type Experiment	Simple Comparison	5	11	5	5	5	10	41
Task Complexity Experiment	Detect Anomaly	1	2	1	1	1	2	21
	Retrieve Value	1	1	1	1	1	2	
	Compute Derived Value	1	1	1	1	1	1	
Dimensionality Experiment	Simple Comparison	2	2	2	1	0	2	15
	Compute Derived Value	0	0	1	2	0	0	
	Correlate	1	1	0	0	0	1	
Visual Elements Experiment	Simple Comparison	12	15	15	7	5	3	83
	Detect Anomaly	2	1	1	3	0	0	
	Retrieve Value	2	1	1	0	4	0	
	Compute Derived Value	3	0	4	2	0	0	
	Correlate	0	1	1	0	0	0	

Table 2 - Visual Elements and their Applicability on Data Visualization Types

Visual Element	Description	Bar	Column	Line	Radar	Pie	Table
Grid Lines	Enables horizontal and vertical grid lines.	X	X	X	X		
Palette 1	Switches visualization to colour Palette 1. A mixture of Tableau's Green-Orange 12 and Blue-Red 6 palettes (Tableau, 2021). Those colors are duller compared to Palette 2.	X	X	X	X	X	
Palette 2	Switches visualization to colour Palette 2. A mixture of Tableau's Green-Orange 12 and Blue-Red 6 palettes (Tableau, 2021). Those colors are brighter compared to Palette 1.	X	X	X	X	X	
Dark Theme	Enables dark background and white text.	X	X	X	X	X	X
Element Size	Changes the default size of primary elements (bars, columns, and lines).	X	X	X	X		
Proximity	Changes the default proximity between primary elements	X	X				

	(bars and columns).						
Data Labels	Displays data values on top of elements (e.g., above bars).	X	X	X	X	X	
Sorting	The data of the visualization are sorted based on a variable.	X	X	X		X	X

Figure 6 - Example of different Visual Elements (ctd.)

3.2 Study Procedure

Due to the implications of the national restrictions in response to the COVID-19 pandemic, it was decided with the partner industry organizations that this study had to be executed in a remote manner. The participants were able to directly access the system as they had already registered accounts on the data collection platform during the previous study (i.e., User Profiling Study). Before initiating any of the analysis tasks, all participants were given a set of demo training analysis tasks, similar but not identical to those of the 4 experiments. This was done to ensure that all participants were familiarized with the experiments' process, minimizing the probability of errors. The participants were also given special instructions as to the minimum screen size and screen resolution that they had to use. This was done to ensure that the study experience was the same across different participants (i.e., avoiding cases where the visualization and/or task controls do not fit in a small screen causing the participant to scroll up and down and thus increasing their cognitive load). Moreover, prior to being able to engage with each of the actual experiments, written instructions were given to the participants indicating the overall experiment process and the approximate amount of time required to complete each experiment (15 minutes on average) etc. The study was conducted for 7 days during which participants had to complete all the experiments with the only constraint being that once an experiment was started it could not be stopped until all tasks were addressed.

During the experiment our system collected (i) the time (in milliseconds) taken by each participant to provide an answer to a specific task, and (ii) the validity of the answer provided. All analysis tasks from each experiment were shown in randomized order ensuring that the task type, visualization type and element type differed between consequent analysis tasks.

4 Impact of Cognitive Factors

In this section we provide an overview of the analysis process applied on the data collected during the user study described in Section 3 and further demonstrate findings regarding the impact of human factors on data visualizations. The extracted knowledge and findings regarding the impact of human factors on data visualizations are broken down and presented in terms of (i) impact on the visualization type and (ii) impact on different visualization elements. Please note the all the code used for analysis purposes is contained in Jupyter notebooks and can be accessed with the link found in APPENDIX 1.

4.1 Preliminary Analysis of Participants' Task Responses

The responses of all 60 participants for all 160 tasks were exported from the data collection system for analysis. Moreover, data preparation took place prior to analysing the data (see notebooks *0.1.vis.tasks.preprocessing_no_missing_data.html* and *0.2.data_prep.html* under the *factors_elements_influence* folder). Initially, for each of the 4 visualization experiments, an analysis of distributions was performed. Boxplots were created for analysing each individual task for all experiments in terms of the performance (milliseconds taken to provide an answer) achieved by all participants. This assisted the team in better understanding performance data distributions for each task, and to investigate problems (e.g., null values, outliers) within a particular task. The system was robust not to produce any null values. However, extreme values were observed and were handled using Tukey's fences, replacing with lower and upper fence values accordingly.

Furthermore, column charts were used to visualize the accuracy (number of people responding correctly to a task) achieved by all participants for each task of each experiment. At the last step of the pre-processing, all responses where a participant provided an incorrect answer were removed.

The remaining sections use the final set of pre-processed data as mentioned above.

4.2 Impact of Human Factors on Data Visualization Type

In this section we present the impact of human factors on data visualization types. The goal of the analysis done at this step (notebook *3.0.factors.ctype.complexity_rank.html* under the *factors_elements_influence* folder) is to explore how different participants (in terms of human factors) perform with a specific data visualization type (e.g., bar chart versus column chart) at different task complexity levels (see Section 3 for a description of task complexity). The results of the analysis are described in in the next subsections.

We start by presenting the analysis procedure. This analysis includes only participants' responses from the first three experiments, excluding responses during the Visual Elements Experiment, which are used in the next section. The analysis process is identical for all human factors, therefore, to facilitate the description, we provide the analysis process only for the Working Memory human factor.

The first step of the process involves dividing the pre-processed data into two groups: participants with (a) High; and (b) Low Working Memory. The groups are further sub-divided according to task complexity (i.e., High, Medium, and Low complexity tasks). This process creates six non-overlapping groups (i.e., datasets), each one representing a level of working memory and a level of task complexity. The steps described next demonstrate how the results of the analysis are transformed into best-fit visualization type rankings, for each combination of Working Memory level and task complexity level. These rankings then generate fuzzy rules, part of the fuzzy rule-based classification system of the adaptation engine described in deliverables D15 and D16.

The three steps below provide insight into each step of the process. Note that the process applied is replicated across all conditions i.e., for all rows of the findings table. The example used to facilitate the description is presented in the first row of Section 4.2.2, where participants with **low** Working Memory have a tendency to perform better with column charts when solving low complexity tasks.

Step 1: first filters all results according to the human factor (in this example, Low Working Memory) and task complexity (in this example, Low Complexity). Next, all performance times for all tasks is aggregated per participant. This yields average performance times for each data visualization type and for each participant.

Step 2: ranks each visualization type for each unique participant according to their average performance for that data visualization type. Essentially, at this step we know for each unique Low Working memory participant which was the best-fit data visualization type with which they performed the best for low complexity tasks.

Step 3: Finally, using the data visualization rankings from all participants we count the number of instances where a specific data visualization type was selected as the best in terms of performance (i.e., the times a chart had the highest rank across all participants). This operation essentially returns a number for each data visualization type. Finally, we transform this set of numbers into a percentage score so that it is normalized across multiple factors. The percentage score is what we see in each row of the finding tables.

4.2.1 OVERALL FINDINGS

This sub-section aims to report on findings that apply across all human factors and task complexity levels with regards to the impact on data visualization types. The next sections report findings that are isolated to a specific human factor at a time (with green are the best visualization types in terms of performance for the given human factor and complexity condition). By inspecting the results of the analysis for every human factor and task complexity level we can see interesting patterns that apply across all human factors. For example, we see that for low and medium complexity tasks the human factor condition does not have an impact on the best-fit data visualization type. Instead, the findings reveal that, for low and medium complexity tasks, the majority of participants (irrespective of human factor) were performing better when using column charts. Moreover, the average score across all human factors for the column chart in low and medium complexity tasks was 55%.

4.2.2 WORKING MEMORY

Working Memory Level	Task Complexity	Visualization Type Score %					
		Bar	Radar	Column	Line	Pie	Table
Low	Low	22	6	67	6	0	0
High		26	5	64	5	0	0
Low	Medium	11	0	78	6	6	0
High		10	0	83	0	7	0
Low	High	6	28	0	11	50	6
High		0	31	17	12	31	10

For high complexity tasks low Working Memory participants seem to have better performance when using the pie chart while high Working Memory participants perform better when utilising either radar graphs or pie charts.

4.2.3 SPEED OF PROCESSING

Speed of Processing Level	Task Complexity	Visualization Type Score %					
		Bar	Radar	Column	Line	Pie	Table
Low	Low	44	0	52	4	0	0
Medium		7	21	64	7	0	0
High		16	0	79	5	0	0
Low	Medium	7	0	78	0	15	0
Medium		14	0	86	0	0	0
High		11	0	84	5	0	0
Low	High	0	41	15	7	33	4
Medium		0	21	21	21	21	14
High		5	21	0	11	53	11

One of the most interesting findings for Speed of Processing is that for high complexity tasks, participants with medium Speed of Processing were equally performing across a variety of visualizations (radar graph, column, line and pie charts) while high and low Speed of Processing participants performed better with pie charts and radar graphs respectively.

4.2.4 CONTROL OF ATTENTION

Control of Attention Level	Task Complexity	Visualization Type Score %					
		Bar	Radar	Column	Line	Pie	Table
Low	Low	35	9	52	4	0	0
Medium		13	6	69	13	0	0
High		24	0	76	0	0	0
Low	Medium	9	0	78	0	13	0
Medium		13	0	81	0	6	0
High		10	0	86	5	0	0
Low	High	0	30	22	9	35	4
Medium		0	38	6	13	38	6
High		5	24	5	14	38	14

Control of Attention has a high correlation with Speed of Processing, and this is also reflected in the above results. The correlation is initially seen in the fact that again participants that have a medium Control of Attention have more data visualizations ranked as the best, in high complexity tasks, when compared to participants with low and high Control of Attention. Moreover, high, and low Control of attention participants were most performant using pie charts during high complexity tasks.

4.2.5 PERCEIVED EXPERTISE

Perceived Experise Level	Task Complexity	Visualization Type Score %					
		Bar	Radar	Column	Line	Pie	Table
Low	Low	25	6	63	6	0	0
Medium		21	5	68	5	0	0
High		33	6	56	6	0	0
Low	Medium	13	0	88	0	0	0
Medium		11	0	89	0	0	0
High		11	0	61	6	22	0
Low	High	0	38	19	0	38	6
Medium		5	26	11	16	42	0
High		0	28	6	17	28	22

For high complexity tasks, participants with high and low Perceived Expertise had best performance with pie charts and radar graphs while people with medium Perceived Expertise had better performance only when using pie charts.

4.2.6 FIELD DEPENDENT – INDEPENDENT (FDI)

FDI Level	Task Complexity	Visualization Type Score %					
		Bar	Radar	Column	Line	Pie	Table
FD	Low	24	7	65	4	0	0
FI		29	0	64	7	0	0
FD	Medium	13	0	83	0	4	0
FI		0	0	79	7	14	0
FD	High	2	28	15	7	37	11
FI		0	50	0	29	21	0

For Field Dependent Independent in high complexity tasks, we can see that participants classified as Field Dependent (FD) had a better overall performance with pie charts, while participants classified as Field Independent (FI) had better overall performance with radar graphs.

4.3 Impact of Human Factors on Data Visualization Elements

In this section, we present the impact of human factors on data visualization elements. The goal of the analysis (notebook *2.0.factors.elements.complexity_perf_gain_auto.html* under the *factors_elements_influence* folder) is to explore how different participants (in terms of human factors) perform when a specific data visualization element (e.g., data labels) is enabled or disabled on the data visualizations at different task complexity levels (task complexity is described in Section 3). Findings of this analysis are presented in Section 4.3.1 and onwards demonstrating the impact (i.e., performance gain) for a group of participants (e.g., low Working Memory) when a specific visual element was enabled in contrast to when it was disabled under a specific task complexity level.

Similarly to the analysis on visualization types, the results were grouped according to the task and visual element, creating 16 groups (8 visual elements for each of the 2 sets of tasks). The first set includes tasks from the Visual Elements Experiment, where the visual element is enabled on the data visualization. We will refer to this set of tasks as the experimental condition. The second set of tasks mirror those in the experimental condition but instead have the visual element disabled. We will refer to those tasks as the control condition. For quickly sampling the sets of tasks (i.e., matching tasks) for each element condition we developed the following procedure (notebook *0.3.element_matching_tasks.html* under the *factors_elements_influence* folder). This procedure also leverages the generated sets of matching tasks for each visual element and further generates an HTML representation of all visualizations that were used in each of the tasks of the Visual Elements Experiment, while for each visual element task the matching control task's visualization is also presented for inspection.

The analysis process for extracting the performance gain for each element across task complexity levels is identical for all human factors. Similarly to the previous section, to facilitate our description, we describe the analysis process only for the Working Memory Human factor. During the first step, the set of pre-processed data is filtered to participants' responses that match the experimental and control tasks for a specific element e.g., proximity. Next, the dataset is divided into two groups i.e., the responses of High, and Low Working Memory participants. Moving on, we have the factor of task complexity (i.e., High, Medium, and Low complexity tasks) which is used to further split each of the two groups of results that were created in the previous step. This process creates six non-overlapping datasets (two levels of Working Memory and three levels of task complexity). At the end, each of the datasets is translated into a factor, indicating the performance gain produced when a visual element is enabled.

The example used to facilitate the description is presented in in Section 4.3.1, where participants with **low** Working Memory have a tendency to perform better when the proximity condition was enabled. The steps below, provide insight on the process mechanisms.

Step 1: The low Working Memory and medium task complexity conditions dataset contains multiple visual element tasks (i.e., experimental condition) and their corresponding control tasks. For each those tasks we record the response time of every low Working Memory participant. Next, the performance of each participant is aggregated for the two sets of tasks. This results in a dataset where for every low Working Memory participant we have their average performance when proximity was enabled and disabled.

Step 2: The final step is to calculate the average performance gain of all participants when enabling or disabling a visual element (in this example, the Proximity element). In addition, we calculate the percentage gain factor.

4.3.1 WORKING MEMORY

Visual Element	Working Memory Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Proximity	Low	Low	9197	9428	-2
	High		8881	10656	-17
	Low	Medium	16009	11052	45
	High		15149	11079	37
	Low	High	42665	14724	190
	High		26042	14198	83

Proximity between bars and columns tends to negatively affect the participants when applied on bar and column charts for simple comparison tasks. More specifically, enabling proximity on simple tasks results in a slight decrease of performance for both High and Low working memory participants; consequently, this visual modification should not be applied in such cases. On the other hand, for medium and high complexity tasks, both low and high working memory participants demonstrate an increase in performance when proximity is applied. This is more evident for high complexity tasks where enabling proximity is highly beneficial for all participants. Moreover, this is true for low working memory participants as their performance increased more drastically (190%) than high working memory participants (83%).

Visual Element	Working Memory Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Element Size	Low	Low	10130	9525	6
	High		9779	10287	-5
	Low	Medium	17793	17841	0
	High		15668	16647	-6
	Low	High	28954	12895	125
	High		29105	12232	138

Changing the size of primary data visualization elements in low and medium complexity tasks did not offer any significant performance gain to low or high working memory participants. On the other hand, the performance gain for both participant groups increased when the size of primary data visualization elements was altered in high complexity tasks.

Visual Element	Working Memory Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Grid Lines	Low	Low	11409	9170	24
	High		11832	9086	30
	Low	Medium	10727	7662	40
	High		10516	6717	57

Enabling grid lines on data visualizations seems to benefit both high and low working memory participants in terms of performance. This effect has slightly higher impact for medium complexity tasks.

Visual Element	Working Memory Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Data Labels	Low	Low	11778	8157	44
	High		10369	7624	36
	Low	Medium	18594	17665	5
	High		17093	19359	-12
	Low	High	10830	33373	-68
	High		11934	41891	-72

Enabling data labels on data visualizations benefits both low and high working memory participants in terms of performance on low complexity tasks. Moreover, we can see that this visual element is more beneficial to low working memory participants as the increase in performance is also shown in medium complexity tasks. On the other hand, high working memory participants have no benefit from this visual element on medium and high complexity tasks since the element causes a decrease in their performance. In conclusion, this visual element should be delivered to all participants in low complexity tasks and only to low working memory participants in medium complexity tasks. Additionally, data labels should be avoided for higher complexity tasks where the chart might also have more data dimensions as the chart tends to get overpopulated with textual information that makes it harder for the participants to process the visual information.

Visual Element	Working Memory Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Dark Theme	Low	Low	15176	10333	47
	High		12860	10127	27
	Low	Medium	8373	8236	2
	High		7676	8708	-12
	Low	High	16637	22305	-25
	High		17179	21539	-20

Enabling the dark theme on data visualizations benefits both low and high working memory participants in terms of performance on low complexity tasks. Moreover, we can see that this visual element is more beneficial to low working memory participants as the increase in performance is also shown in medium complexity tasks. Instead, high working memory participants have no benefit from this visual element since the element results in a decrease in their performance in both medium and high complexity tasks. In conclusion, this visual element should be delivered to all participants in low complexity tasks and only to low working memory participants in medium complexity tasks. Additionally, the dark theme should be avoided for higher complexity tasks.

Visual Element	Working Memory Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Sorting	Low	Low	9902	7528	32
	High		9337	7434	26

	Low	Medium	19325	14717	31
	High		16438	13517	22
	Low	High	24463	14766	66
	High		25598	13707	87

Sorting the data on a data visualization proved to be beneficial in terms of performance for both low and high working memory participants across all levels of task complexity. While the performance gain across low and medium complexity tasks is similar for the two groups of participants, the low working memory participants seem to have benefited slightly more. On the other hand, we see that sorting data on high complexity tasks becomes even more essential for both groups of participants as their performance gains increase more drastically yielding performance that is close to what the two groups achieved when solving medium complexity tasks. It must be noted that in high complexity tasks, sorting data aids high working memory participants achieve a higher increase in performance than low working memory participants.

Visual Element	Working Memory Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Palette 1	Low	Low	11613	9273	25
	High		11046	9209	20
	Low	Medium	14959	15625	-4
	High		13727	11878	16
	Low	High	34982	12951	170
	High		42960	15286	181

Changing the colour palette setting on the data visualizations to Palette 1 aided participants achieve a higher performance across all levels of task complexity. While on low complexity tasks the two groups of participants achieve very similar results, we can see that on medium complexity tasks this intervention does not benefit low working memory participants. Moving on, with increase in task complexity (i.e., high task complexity) we can see that the new colour palette becomes essential as it provides a much higher increase in performance for both groups of participants.

Visual Element	Working Memory Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Palette 2	Low	Low	13177	9001	46
	High		11426	8616	33
	Low	Medium	14815	17378	-15
	High		13252	16868	-21
	Low	High	14766	9452	56
	High		16046	8667	85

Applying the second colour palette (Palette 2) to our data visualizations at low complexity tasks helps both participant groups achieve better performance, and this more evident for low working memory participants. With regards to medium complexity tasks this intervention seems to be inappropriate for both groups of participants as it degrades their performance. Finally, for high task complexity, we can see that colour Palette 2 (similar to low complexity tasks) is essential as it provides an increase in performance for both groups of participants, especially to high working memory participants.

4.3.2 SPEED OF PROCESSING

Visual Element	Speed of Processing Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Proximity	Low	Low	9311	12617	-26
	Medium		8587	8671	-1
	High		8727	8193	7
	Low	Medium	16811	12897	30
	Medium		13145	9814	34
	High		14820	9441	57
	Low	High	36220	18350	97
	Medium		13863	8090	71
	High		27110	9396	189

We can observe that added proximity between elements of bar and column charts is especially helpful to those participants with high level of speed of processing as these participants seem to have an increased performance across all levels of task complexity, much higher than other groups of participants. Additionally, for low and medium level of speed of processing groups of participants this intervention should not be used on low complexity tasks as it is ineffective in terms of performance. Moreover, for medium complexity tasks these latter groups of participants seem to benefit when proximity is enabled.

Visual Element	Speed of Processing Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Element Size	Low	Low	10872	11747	-7
	Medium		8960	9830	-9
	High		9209	7680	20
	Low	Medium	19689	19336	2
	Medium		14947	16290	-8
	High		12924	14480	-11
	Low	High	33907	14085	141
	Medium		21176	11376	86
	High		26741	10152	163

Changing the size of primary data visualization elements in low and medium complexity tasks in general did not offer any significant performance benefit to participants. The only distinction is that in low complexity tasks participants with a high level of speed of processing were slightly benefited in terms of performance. On the other hand, the performance for all participant groups increased when the size of primary data visualization elements was altered in high complexity tasks. This latter effect is particularly evident for participants with low and high levels of speed of processing.

Visual Element	Speed of Processing Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Grid Lines	Low	Low	13250	10602	25
	Medium		10276	8198	25
	High		10556	7609	39
	Low	Medium	10996	8145	35
	Medium		9869	6324	56
	High		10351	5841	77

Enabling grid lines on data visualizations benefits all groups of participants in terms of performance on low and medium complexity tasks. Moreover, we can see that this visual element is more beneficial to participants with high levels of speed of processing as they demonstrated a higher increase in performance than the other participant groups. Additionally, the above results reveal a trend that demonstrates the interaction of speed of processing levels and the increase in performance while the task complexity increases. Essentially as the task complexity increases participants with higher levels of speed of processing demonstrate higher performance gains when the grid lines are enabled on the data visualization. This can be expressed as a positive correlation between task complexity level, speed of processing level and performance gain.

Visual Element	Speed of Processing Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Data Labels	Low	Low	11359	9128	24
	Medium		10546	7028	50
	High		10173	6565	55
	Low	Medium	17991	21217	-15
	Medium		15635	14593	7
	High		18065	18618	-3
	Low	High	13862	55416	-75
	Medium		9310	27760	-66
	High		9555	15381	-38

Enabling data labels on data visualizations benefits all groups of participants in terms of performance on low complexity tasks and especially the medium and high speed of processing participant groups. Moreover, we can see that this visual element is also beneficial to participants with medium level of speed of processing as the increase in performance is also shown in medium complexity tasks. Instead, with regards to medium complexity tasks the rest of the participant groups have no benefit from this visual element since it causes a decrease in their performance. Generally, this visual element should be delivered to all participants in low complexity tasks (especially to those of higher speed of processing levels), and only to medium speed of processing participants in medium complexity tasks. Additionally, data labels should be avoided for higher complexity tasks where the chart might also have more data dimensions as the chart tends to get overpopulated with textual information that makes it harder for the participants to process the visual information.

Visual Element	Speed of Processing Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Dark Theme	Low	Low	14189	11619	22
	Medium		12520	9716	29
	High		13416	8487	58
	Low	Medium	8363	9536	-12
	Medium		7494	6920	8
	High		7598	8484	-10
	Low	High	19160	24292	-21
	Medium		15671	25750	-39
	High		14863	15102	-2

Enabling the dark theme on data visualizations benefits all groups of participants in terms of performance on low complexity tasks and especially the medium and high speed of processing participant groups. Moreover, we can see that the dark theme is also beneficial to participants with medium level of speed of processing as the increase in performance is also shown in medium complexity tasks. Instead, with regards to medium complexity tasks the rest of the participant groups have no benefit from this intervention since it causes a decrease in their performance. Generally, the dark theme should be delivered to all participants in low complexity tasks (especially to those of higher speed of processing levels), and only to medium speed of processing participants in medium complexity tasks. Additionally, the dark theme should be avoided for higher complexity tasks.

Visual Element	Speed of Processing Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Sorting	Low	Low	10040	8754	15
	Medium		9401	6987	35
	High		8825	6045	46
	Low	Medium	18387	15274	20
	Medium		15227	14072	8
	High		17163	12791	34
	Low	High	27465	15999	72
	Medium		24306	12046	102
	High		22211	12518	77

Sorting the data on a data visualization proved to be beneficial in terms of performance for all speed of processing participant groups across all levels of task complexity. At low complexity tasks we can see the performance gain increasing linearly as the level of speed of processing increases. This effect though is not repeated at higher complexity levels since participants with medium speed of processing show a decreased performance gain in tasks of medium complexity while they show a huge increase in performance gain (much higher than other participant groups) in high complexity tasks. Essentially, sorting data on visualizations can be useful for all speed of processing participant groups especially at the higher complexity tasks.

Visual Element	Speed of Processing Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Palette 1	Low	Low	11900	10253	16
	Medium		10937	8674	26
	High		10240	8164	25
	Low	Medium	14392	15989	-10
	Medium		13417	11247	19
	High		13999	11049	27
	Low	High	50923	16501	209
	Medium		36971	13340	177
	High		31629	12508	153

Changing the colour palette setting on the data visualizations to Palette 1 helped participants achieve a higher performance across all levels of task complexity except for low speed of processing participants at medium complexity tasks. It is interesting how the change in colour palette in low and medium complexity tasks helps medium and high speed of processing participants achieve a higher performance gain than those participants with low level of speed of processing. Moreover, this effect changes at the high complexity tasks as there is a negative correlation between speed of processing levels and performance gain, meaning that participants with lower levels of speed of processing in high complexity tasks receive more performance gain than those with higher levels of speed of processing.

Visual Element	Speed of Processing Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Palette 2	Low	Low	12937	10149	27
	Medium		10681	8617	24
	High		11487	6773	70
	Low	Medium	14022	18626	-25
	Medium		13768	19666	-30
	High		13418	12816	5
	Low	High	17650	10216	73
	Medium		14447	8485	70
	High		13594	7345	85

Changing the colour palette setting on the data visualizations to Palette 2 generally helped participants achieve a higher performance across low and high levels of task complexity. It is interesting that the high speed of processing group of participants received the most benefit in terms of performance across all task complexity levels with Palette 2 when compared to the other two participant groups (this effect is also true in the medium complexity tasks). In general, we can conclude that this palette can be of higher benefit to participants with high levels of speed of processing across low and medium complexity tasks, while it can strongly benefit all participant groups in high complexity tasks.

4.3.3 CONTROL OF ATTENTION

Visual Element	Control of Attention Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Proximity	Low	Low	10102	12460	-19
	Medium		8573	9228	-7
	High		8028	8739	-8
	Low	Medium	17429	13024	34
	Medium		12679	8660	46
	High		15202	10741	42
	Low	High	36752	17885	105
	Medium		21976	13023	69
	High		27311	9821	178

Added proximity between elements of bar and column charts for tasks of low complexity does not benefit any of the participants with regards to their control of attention level. Moreover, the effect of proximity seems to be beneficial for all participant groups in terms of performance in medium and high complexity tasks. We conclude that proximity should be applied on data visualizations on higher complexity tasks for all groups of participants and especially for those with higher levels of control of attention.

Visual Element	Control of Attention Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Element Size	Low	Low	11124	12411	-10
	Medium		9527	9309	2
	High		8783	7999	10
	Low	Medium	17734	19942	-11
	Medium		15890	16621	-4
	High		14860	14190	5
	Low	High	36756	15289	140
	Medium		21147	12537	69
	High		28851	9199	214

Changing the size of primary data visualization elements in low and medium complexity tasks in general did not offer any significant performance benefit to participants. The only exception is that for low and medium complexity tasks, participants with a high level of control of attention were slightly benefited in terms of performance. On the other hand, the performance for all participant groups increased when the size of primary data visualization elements was altered in high complexity tasks. This latter effect is more evident for participants with low and high levels of control of attention.

Visual Element	Control of Attention Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Grid Lines	Low	Low	14305	10633	35

	Medium		10051	8494	18
	High		10118	7872	29
	Low	Medium	12251	8280	48
	Medium		9191	6516	41
	High		9978	5989	67

Enabling grid lines on data visualizations benefits all groups of participants in terms of performance on low and medium complexity tasks. Moreover, we can see that this visual element is more beneficial to (i) participants with low levels of control of attention in low complexity tasks and (ii) to participants with high levels of control of attention in high complexity tasks. We can conclude that for simpler tasks this intervention is essential for participants with low levels of control of attention. Moreover, in complex tasks this intervention quickly becomes a necessity for participants with higher levels of control of attention as well.

Visual Element	Control of Attention Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Data Labels	Low	Low	12058	9309	30
	Medium		10130	6845	48
	High		9720	6811	43
	Low	Medium	20224	21498	-6
	Medium		14159	17769	-20
	High		18667	16710	12
	Low	High	13913	49359	-72
	Medium		9872	44730	-78
	High		9686	12049	-20

Enabling data labels on data visualizations benefits all groups of participants in terms of performance on low complexity tasks and especially the medium and high control of attention participant groups. Moreover, we can see that this visual element is also beneficial to participants with high level of control of attention as the increase in performance is also shown in medium complexity tasks. Instead, with regards to medium complexity tasks the rest of the participant groups have no benefit from this visual element since it causes a decrease in their performance. In conclusion, this visual element should be delivered to all participants in low complexity tasks (especially to those of higher control of attention levels), and only to high control of attention participants in medium complexity tasks. Additionally, data labels should be avoided for higher complexity tasks where the chart might also have more data dimensions as the chart tends to get overpopulated with textual information that makes it harder for the participants to process the visual information.

Visual Element	Control of Attention Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Dark Theme	Low	Low	15057	11925	26
	Medium		11971	9625	24
	High		12863	8551	50

	Low	Medium	8274	9574	-14
	Medium		7138	7322	-3
	High		8086	8207	-1
	Low	High	19980	24474	-18
	Medium		17309	24422	-29
	High		13631	16994	-20

Enabling the dark theme on data visualizations benefits all groups of participants in terms of performance on low complexity tasks and especially the participants with high level of control of attention. Generally, the dark theme should be delivered to all participants in low complexity tasks (especially to those of higher control of attention levels) and be avoided for all control of attention participant groups in higher complexity tasks.

Visual Element	Control of Attention Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Sorting	Low	Low	10991	9040	22
	Medium		8213	6625	24
	High		8733	6267	39
	Low	Medium	20062	15686	28
	Medium		14164	12867	10
	High		17433	13468	29
	Low	High	28366	15219	86
	Medium		24357	12972	88
	High		22571	13278	70

Sorting the data on a data visualization proved to be beneficial in terms of performance for all control of attention participant groups across all levels of task complexity. At low complexity tasks we can see the performance gain increasing linearly as the level of control of attention increases. This effect though is not repeated at medium complexity tasks since participants with medium control of attention show a decreased performance gain compared to other participant groups. Additionally, the impact on low complexity tasks disappears in high complexity tasks since participants with high level of control of attention tend to have lower performance gain than other participant groups. We can conclude that sorting data on visualizations can be useful for all control of attention participant groups especially at the higher complexity tasks.

Visual Element	Control of Attention Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Palette 1	Low	Low	13098	10710	22
	Medium		9643	8359	15
	High		10024	8131	23
	Low	Medium	15889	16738	-5
	Medium		11737	10970	7
	High		14282	10694	34

	Low	High	46584	15905	193
	Medium		37321	13099	185
	High		37547	13829	172

Changing the colour palette setting on the data visualizations to Palette 1 aided participants achieve a higher performance across all levels of task complexity except for low control of attention participants at medium complexity tasks. Moreover, we see an interesting effect at the high complexity tasks as participants with lower levels of control of attention in high complexity tasks receive more performance gain than those with higher levels of control of attention.

Visual Element	Control of Attention Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Palette 2	Low	Low	13430	10449	29
	Medium		10982	8447	30
	High		10746	7038	53
	Low	Medium	15481	20169	-23
	Medium		12227	14652	-17
	High		13669	16220	-16
	Low	High	18326	10620	73
	Medium		14941	8421	77
	High		13062	7389	77

Changing the colour palette setting on the data visualizations to Palette 2 generally helped participants achieve a higher performance across low and high levels of task complexity. It is interesting that the high control of attention group of participants received the most benefit in terms of performance, in the low complexity tasks with Palette 2 when compared to the other two participant groups. In general, we can conclude that this palette can significantly aid participants with high levels of control of attention in low complexity tasks, while it can strongly benefit all participant groups in high complexity tasks.

4.3.4 PERCEIVED EXPERTISE

Visual Element	Perceived Experise Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Proximity	Low	Low	9740	9747	0
	Medium		8115	9578	-15
	High		8960	10125	-12
	Low	Medium	14436	9476	52
	Medium		16027	11332	41
	High		14803	10808	37
	Low	High	37275	19093	95
	Medium		20199	11664	73
	High		23421	9749	140

The above results reveal that added proximity between elements of bar and column charts is particularly useful for participants of all expertise levels at medium and high levels of task complexity, but not at low level complexity tasks. At medium complexity tasks we can see the performance gain decreasing as the expertise of the participant increases, while on high complexity tasks participants with high expertise are also highly benefited from the added proximity. Adding proximity on a chart used for low complexity tasks is very useful for participants with lower expertise levels. Additionally, proximity becomes a necessity for participants of higher expertise as well when the task becomes more difficult.

Visual Element	Perceived Experise Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Element Size	Low	Low	9848	10261	-4
	Medium		8300	9134	-9
	High		10611	10006	6
	Low	Medium	16899	17579	-4
	Medium		15528	17479	-11
	High		16650	15923	5
	Low	High	35058	13857	153
	Medium		25341	12653	100
	High		27450	10890	152

Changing the size of primary data visualization elements in low and medium complexity tasks in general proved to not offer any significant performance benefit to participants. The only distinction is that in low and medium complexity tasks participants with a high expertise were slightly benefited in terms of performance. On the other hand, the performance for all participant groups increased when the size of primary data visualization elements was altered in high complexity tasks. This latter effect is especially true for participants with low and high levels of expertise.

Visual Element	Perceived Experise Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Grid Lines	Low	Low	11597	9393	23
	Medium		10787	8691	24
	High		11820	9011	31
	Low	Medium	10927	7521	45
	Medium		10098	6382	58
	High		10296	7007	47

Enabling grid lines on data visualizations benefits all groups of participants in terms of performance on low and medium complexity tasks. Moreover, we can see that this visual element is more beneficial to (i) participants with high expertise in low complexity tasks and (ii) to participants with medium expertise in high complexity tasks. We can conclude that in general this intervention is necessary for visualizations regardless of complexity and participant expertise. It must be noted though that with task complexity increasing the necessity for this intervention is more evident.

Visual Element	Perceived Experise Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Data Labels	Low	Low	11376	8159	39
	Medium		9693	7647	27
	High		10946	7527	45
	Low	Medium	16926	21233	-20
	Medium		18789	17430	8
	High		16762	17708	-5
	Low	High	12472	24895	-50
	Medium		8608	33624	-74
	High		12469	39776	-69

Enabling data labels on data visualizations benefits all groups of participants in terms of performance on low complexity tasks and especially the low and high expertise participant groups. Moreover, we can see that this visual element is also beneficial to participants with medium level of expertise as the increase in performance is also shown in medium complexity tasks. Instead, with regards to medium complexity tasks the rest of the participant groups have no benefit from this visual element since it causes a decrease in their performance. Overall, this visual element should be delivered to all participants in low complexity tasks, and only to participants of medium expertise in medium complexity tasks. Additionally, data labels should be avoided for higher complexity tasks where the chart might also have more data dimensions as the chart tends to get overpopulated with textual information that makes it harder for the participants to process the visual information.

Visual Element	Perceived Experise Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Dark Theme	Low	Low	13988	10566	32
	Medium		11984	9630	24
	High		13951	10264	36
	Low	Medium	7199	8628	-17
	Medium		6739	7518	-10
	High		9361	8327	12
	Low	High	18820	24157	-22
	Medium		16478	20960	-21
	High		16283	19763	-18

Enabling the dark theme on data visualizations benefits all groups of participants in terms of performance on low complexity tasks. Moreover, as the complexity of the task increases only high expertise participants demonstrate an increase in performance, as demonstrated in the medium complexity tasks. Generally, the dark theme should be delivered to all participants in low complexity tasks, to high expertise participants in medium complexity tasks and be avoided for all remaining task complexity and participant expertise conditions.

Visual Element	Perceived Experise Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Sorting	Low	Low	9953	7574	31
	Medium		8700	7196	21
	High		9162	7636	20
	Low	Medium	17337	13645	27
	Medium		17859	13171	36
	High		17020	14902	14
	Low	High	27573	14732	87
	Medium		24783	13319	86
	High		23496	13929	69

Sorting the data on a data visualization proved to be beneficial in terms of performance for all levels of expertise across all levels of task complexity. At all task complexity levels we can see the performance gain decreasing linearly as the level of expertise increases. The only point where we do not see this trend is on medium complexity tasks where the medium expertise participants demonstrate higher performance gain than low expertise participants. In general, we can conclude that sorting is especially necessary for the low expertise participants on all levels of task complexity, for the medium expertise participants on medium and high levels of task complexity, and for high expertise participants sorting is necessary mostly on high complexity tasks.

Visual Element	Perceived Experise Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Palette 1	Low	Low	11541	9088	27
	Medium		10103	8712	16
	High		10787	9701	11
	Low	Medium	15611	13724	14
	Medium		13641	11368	20
	High		12323	13804	-11
	Low	High	44996	18547	143
	Medium		35116	10862	223
	High		40378	13049	209

Changing the colour palette setting on the data visualizations to Palette 1 helped participants achieve a higher performance across all levels of task complexity except for high expertise participants at medium complexity tasks. The major performance gain effect is more evident at high complexity tasks.

Visual Element	Perceived Experise Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)

Palette 2	Low	Low	12403	8732	42
	Medium		10207	8252	24
	High		12544	8850	42
	Low	Medium	15409	18762	-18
	Medium		13373	14415	-7
	High		12026	15927	-24
	Low	High	15674	9244	70
	Medium		15276	8362	83
	High		14799	9174	61

Changing the colour palette setting on the data visualizations to Palette 2 overall aided participants achieve a higher performance across low and high levels of task complexity. On low and high complexity tasks this palette can help increase the performance of the low and high expertise participant groups while in high complexity tasks, medium expertise participants also experience a significant increase in performance gain.

4.3.5 FIELD DEPENDENT – INDEPENDENT (FDI)

Visual Element	FDI Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Proximity	FD	Low	9182	10664	-14
	FI		8260	9086	-9
	FD	Medium	14379	11160	29
	FI		18690	10582	77
	FD	High	29012	14304	103
	FI		31202	14511	115

Proximity between bars and columns seems to negatively affect the participants when used on bar and column charts for simple comparison tasks. More specifically, enabling proximity on simple tasks results in a slight decrease of performance for both Field Dependent (FD) and Field Independent (FI) participants meaning that this visual modification should not be applied in such cases. On the other hand, when it comes to tasks of medium and high complexity, both FD and FI participants demonstrate an increase in performance when proximity is enabled. This is more evident for high complexity tasks, where enabling proximity is of high benefit to all participants. Moreover, proximity is extremely important for FI participants since they demonstrate higher performance increase in both medium and high complexity tasks compared to FD participants when proximity was enabled.

Visual Element	FDI Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Element Size	FD	Low	10115	10147	0
	FI		9026	9619	-6
	FD	Medium	16907	16926	0
	FI		14603	17543	-17

	FD	High	31333	12863	144
	FI		23546	10394	127

Changing the size of primary data visualization elements in low and medium complexity tasks proved to not offer any significant performance benefit to FD or FI participants. On the other hand, the performance for both participant groups increased when the size of primary data visualization elements was altered in high complexity tasks.

Visual Element	FDI Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Grid Lines	FD	Low	12212	9252	32
	FI		10039	8446	19
	FD	Medium	10542	7013	50
	FI		10543	7013	50

Enabling grid lines on data visualizations seems to benefit both FD and FI participants in terms of performance. This effect has slightly higher impact for medium complexity tasks.

Visual Element	FDI Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Data Labels	FD	Low	11211	7955	41
	FI		9423	7342	28
	FD	Medium	17178	19284	-11
	FI		19208	17861	8
	FD	High	11972	39439	-70
	FI		8864	40210	-78

Enabling data labels on data visualizations benefits FD and FI participants in terms of performance on low complexity tasks. Moreover, we can see that this visual element is more beneficial to FI participants as the increase in performance is also shown in medium complexity tasks. On the other hand, FD participants have no benefit from this visual element on medium and high complexity tasks since the element causes a decrease in their performance. Generally, this visual element should be delivered to all participants in low complexity tasks and only to FI participants in medium complexity tasks. Additionally, data labels should be avoided for higher complexity tasks where the chart might also have more data dimensions as the chart tends to get overpopulated with textual information that makes it harder for the participants to process the visual information.

Visual Element	FDI Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Dark Theme	FD	Low	14080	10280	37
	FI		11828	9704	22
	FD	Medium	7823	8538	-8
	FI		8164	8485	-4
	FD	High	17319	21911	-21

	FI		15902	21119	-25

Enabling the dark theme is beneficial in terms of performance for FD and FI participants only on low complexity tasks. This effect seems to be stronger for FD participants.

Visual Element	FDI Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Sorting	FD	Low	9958	7614	31
	FI		8005	7002	14
	FD	Medium	16644	14018	19
	FI		19602	14032	40
	FD	High	25534	14364	78
	FI		24148	12759	89

Sorting the data on a data visualization proved to be beneficial in terms of performance for both FD and FI participants across all levels of task complexity. Moreover, the performance gain across low complexity tasks is higher for FD participants and in medium complexity tasks is higher for FI participants. On the other hand, we see that sorting data on high complexity tasks becomes even more important for both groups of participants as their performance gains increase more drastically. It can also be observed that FD participants benefit from sorting early on the process with low complexity tasks, while for FI participants, the requirement for sorting data becomes more prominent on more complex tasks.

Visual Element	FDI Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Palette 1	FD	Low	11739	9253	27
	FI		9497	8906	7
	FD	Medium	14555	13743	6
	FI		12702	10892	17
	FD	High	42242	15437	174
	FI		38418	11144	245

Changing the colour palette setting on the data visualizations to Palette 1 helped participants achieve a higher performance across all levels of task complexity. On low complexity tasks FD participants have a higher gain in performance than FI participants, while on medium complexity tasks we can see the reverse effect taking place. Moving on, with increase in task complexity (i.e., high task complexity) we can see that the new colour palette becomes essential as it provides a much higher increase in performance for both groups of participants.

Visual Element	FDI Level	Task Complexity	Element Disabled (ms)	Element Enabled (ms)	Performance Gain (%)
Palette 2	FD	Low	12440	8935	39
	FI		10346	8062	28
	FD	Medium	14414	18166	-21
	FI		12029	13676	-12

	FD	High	15957	9037	77
	FI		14597	8461	73

Applying the second colour palette (Palette 2) to our data visualizations at low complexity tasks helps both participant groups achieve better performance. With regards to medium complexity tasks this intervention seems to be inappropriate for both groups of participants as it degrades their performance. Moving on, with increase in task complexity (i.e., high task complexity) we can see that colour Palette 2 becomes even more essential as it provides an increase in performance for both groups of participants helping them achieve performance similar to that of low complexity tasks.

4.3.6 DISCUSSION ON THE EFFECT OF DIFFERENT ELEMENTS

In this subsection we summarise the most interesting findings regarding the effect of individual visual elements with regards to the participants' performance across human factors.

Proximity: In general, enabling the visual element of proximity on bar and column charts has proven beneficial in terms of performance for all participants with regards to medium and high complexity tasks. This element should generally be avoided for low complexity tasks because all participants across most human factor groups for low complexity tasks were negatively affected or received no performance benefit. The only group of participants that received a benefit with proximity enabled in low complexity tasks were those of high levels of speed of processing.

Element Size: This element is best enabled for when the complexity of the task is high. We have seen that for medium and low complexity tasks this visual element provided minimal or no benefit to the majority of participants, while in many cases it caused degradation of performance. The performance effects of element size in low and medium complexity tasks are always affected by the human factor level under consideration, but the majority of results reveal that there is no significant positive performance effect. Cases where we see a positive performance effect for low and medium complexity tasks, the performance gain is usually lower than 10%. On the other hand, altering the element size for high complexity tasks proved to be extremely beneficial in terms of performance for all participants, most of the times reaching a performance gain of higher than 100%.

Grid Lines: Our results prove that grid lines are essential for data visualizations. We notice that regardless of human factor, enabling grid lines helped our participants achieve a significantly better performance across all task complexity levels. Moreover, the necessity of grid lines on data visualizations was becoming more prominent as the complexity of the task increased. This effect can be seen across all human factors by the linear increase of performance gain experienced by participants as the task complexity was increasing.

Data Labels: Enabling the data label was found to be beneficial for participants in terms of performance, specifically in low complexity tasks across all human factors. Moreover, the opposite effect was present for high complexity tasks, where the element's presence was always negatively affecting the participants' performance. With regards to medium complexity tasks, this element was mostly negatively affecting the participants performance as well, except for some minor cases where it provided a very slight increase in performance (usually a gain below 10%).

The slight increase in performance for medium complexity tasks is affected by the different human factors.

Dark Theme: Very similar to the Data Labels element, Dark Theme is best enabled for low complexity tasks since it was found to be beneficial for participants in terms of performance for this task complexity. Moreover, the opposite effect was present for high complexity tasks, where the dark theme was always negatively affecting the participants' performance. With regards to medium complexity tasks, the dark theme was mostly negatively affecting the participants performance as well, except for some minor cases where it provided a very slight increase in performance. Those cases include participants with medium level of speed of processing (8% performance gain) and participants with high perceived expertise (12% performance gain).

Sorting: Our findings show that the sorting element (i.e., providing sorted series on data visualizations) was beneficial for participants in terms of performance across all complexity levels and human factors. The effect was more evident for high complexity tasks where the performance gain of the participants was much greater compared to that achieved for medium or low complexity tasks. Additionally, it must be noted that task complexity did not necessarily affect performance gain in a linear fashion since for many medium complexity tasks the gain would be lower than that of low complexity tasks, depending on the human factor. Regardless, performance gains achieved for high complexity tasks were always exceedingly higher than those achieved for the rest of complexity levels.

Palette 1 and 2: When comparing the effect of the two palettes in terms of performance gain achieved by participants, we can see that in general the duller Palette 1 enabled our participants to achieve much higher gains in performance for medium and high complexity tasks across human factors. Specifically, for Palette 1 performance gains were usually positive for medium complexity tasks, while for the brighter Palette 2 this was not the case since as most participants were negatively affected by the use of this palette in medium complexity tasks. Moreover, it must be noted that for the brighter Palette 2 the performance gain between for high complexity tasks did not deviate significantly from the gain achieved on low complexity task. On the other hand, for the duller Palette 1 performance gains for higher complexity tasks were exceedingly higher than those of lower complexity tasks across all human factors.

Conclusions

This deliverable presented the overall approach taken for discovering the impact of human factors on data visualizations. Through this deliverable we demonstrated the key human factors which make up an essential part of the IDEALVis user model, we explained why those were selected for our analysis, and we also demonstrated how those human factors were analysed for achieving the segmentation of our participants in different groups, required for exploring the impact of factors on data visualizations.

We illustrated the design of the Data Visualization User study (i.e., User Study 2) which enabled us to capture all the required data for further exploring the impact of human factors on data visualizations. The design of the study illustrated the different data visualizations which we explored and the different visual elements. Moreover, through the user study design we defined the different types of analytical tasks and task complexity levels which were used. Describing the human factors of interest and the user study's design laid the foundation and direction towards demonstrating the steps taken to explore the impact of human factors. After presenting the analysing steps on the performance data of the participants captured from the user study, we illustrated some key findings with regards to the impact of human factors on data visualization types and specific data visualization elements across the three task complexity levels.

APPENDIX 1: Analysis Notebooks

All IDEALVis Analysis Notebooks are found at this Link.