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User Experience (UX) based on Data Visualization

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Abstract

It is critical to build tools to study data in an environment where data is rapidly being gathered and utilized. Visualizing the data may help with this. The usefulness and efficiency of such informational visualizations are often examined, but hedonic elements such as sheer delight and aesthetic beauty are typically overlooked. These characteristics are included in the idea of user experience (UX), which is a good predictor of a user's overall rating of an information visualization. However, since the discipline is very new and has diverse definitions, there are many different approaches to measure UX. The goal of this exploratory study was to see whether the CUE (elements of user experience) paradigm and its measurement tool, meCUE, are adequate for assessing the UX for data visualization. This study looked at the user experience of information visualizations with minor differences in terms of animation features to investigate whether UX metrics might explain user preferences. Small differences in the experiment couldn't be seen by using the meCUE technique, hence descriptive study seems to be more appropriate in this case. Because the meCUE method failed to pick up on even the smallest differences in the trial, descriptive study seems to be the better option in this case. The findings demonstrate the subjective nature of UX and highlight the need of defining a user group. The findings also show that rather of depending just on a user's self-report, UX assessment should include research interpretation and objectivity.

Аңдатпа

Деректер көбірек жиналып, пайдаланылып жатқан әлемде оны зерттеу әдістері әзірлеу де маңызды. Мұны деректерді визуализациялау арқылы жасауға болады. Мұндай ақпаратты визуализацияның сапасы көбінесе пайдалану сапасы мен эстетикалық сапа сияқты гедоникалық факторларды елемейтін, ыңғайлылық көрсеткіштерінің тиімділігі мен тиімділігімен өлшенеді. Пайдаланушы тәжірибесі тұжырымдамасы (UX) осы факторларды қамтиды және пайдаланушының ақпаратты визуализациялаудың жалпы рейтингінің жақсы болжаушысы болып табылады. Дегенмен, UX өлшеудің көптеген жолдары бар, өйткені өріс әлі жас және көптеген анықтамалары бар. Бұл алдын ала зерттеу CUE (пайдаланушы тәжірибесінің құрамдас бөліктері) моделі мен оның деректер визуализациясының UX деңгейін өлшеуге перспективалы үміткерлер болып табылатын meCUE өлшеу құралының деректерді визуализациялау доменіне шынымен сәйкес келетінін зерттеді. Атап айтқанда, бұл зерттеу UX ұпайлары пайдаланушы қалауларын түсіндіре алатынын көру үшін анимациялық элементтер тұрғысынан шағын ауытқулары бар ақпараттық визуализациялардың UX өлшемін өлшеді. meCUE әдісі эксперименттегі нәзік айырмашылықтарды өлшей алмады, бұл жағдайда сапалы зерттеулер тиімдірек болып көрінеді. Нәтижелер UX субъективтілігін көрсетеді және пайдаланушылар тобын көрсетудің маңыздылығын көрсетеді. Нәтижелер сонымен қатар UX бағалауы пайдаланушының өзіндік есебіне ғана емес, зерттеудің интерпретациясы мен объективтілігіне сүйенгенде пайдалы болуы мүмкін екенін көрсетеді.

Аннотация

В мире, где данные собираются и используются все чаще, важно также разработать способы изучения этих данных. Это можно сделать, визуализировав данные. Качество таких информационных визуализаций часто измеряется с помощью показателей эффективности и эффективности использования, в которых отсутствуют такие гедонистические факторы, как радость от использования и эстетическое качество. Концепция пользовательского опыта (UX) действительно включает эти факторы и является хорошим предиктором для общей оценки визуализации информации пользователем. Однако существует множество способов измерения потока, поскольку эта область все еще молода и имеет множество определений. В этом исследовательском исследовании изучалось, действительно ли модель CUE (компоненты пользовательского опыта) и ее инструмент измерения meCUE, которые были признаны многообещающими кандидатами для измерения потока визуализации данных, подходят для области визуализации данных. В частности, в этом исследовании измерялся поток информационных визуализаций, которые имели небольшие отклонения с точки зрения анимированных элементов, чтобы выяснить, могут ли показатели потока объяснить предпочтения пользователей. Метод meCUE не смог измерить тонкие различия в эксперименте, и в этом случае качественное исследование, по-видимому, превосходит его. Результаты показывают субъективность пользовательского интерфейса и подчеркивают важность указания группы пользователей. Результаты также предполагают, что оценка UX может выиграть от того, что она не будет полагаться исключительно на самоотчет пользователя, а будет включать интерпретацию результатов исследования и объективность.

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To my family

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1. Introduction

The quantity of data in society is continually increasing. Data comes from a variety of places, including social networking sites, transactional data, and internet activities. IBM estimates that 250 million gigabytes of data are generated each day. According to IDC, 163 trillion GB of data will be generated in 2025 (Figure 1.1).[5] The challenge is how to turn this massive volume of data into knowledge and insights.

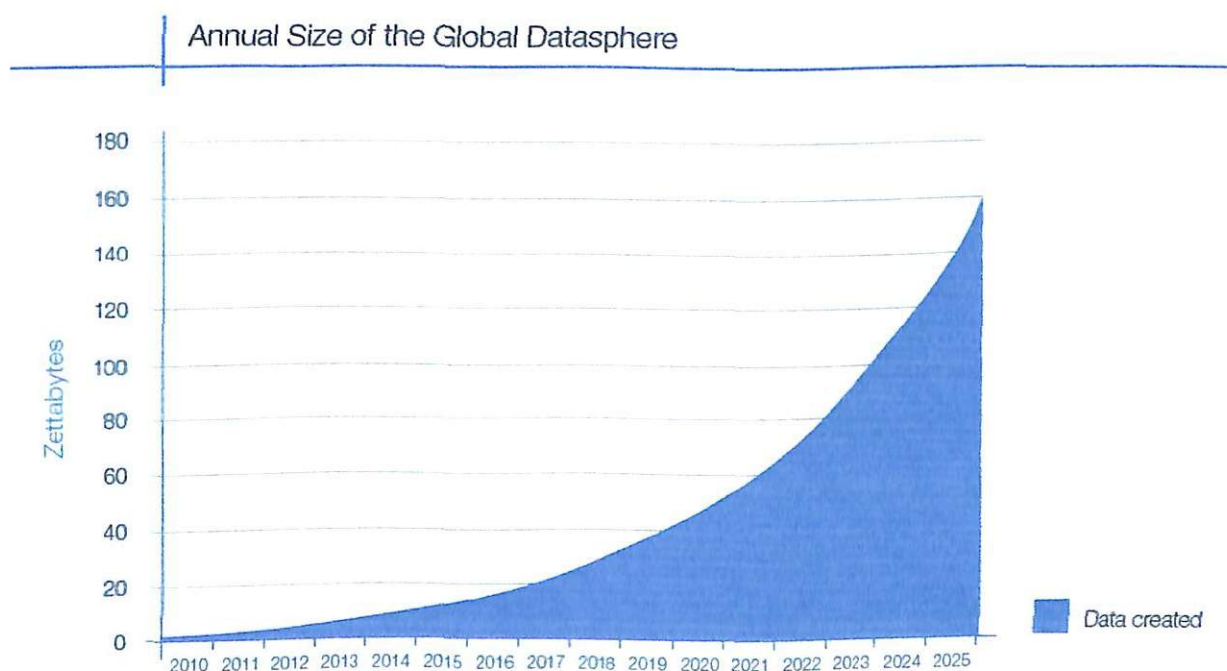


Figure 1.1: IDC’s estimate of the total quantity of data produced in the future

Techniques for gathering and handling this data are receiving a lot of attention, and the technology is constantly advancing. However, there is a lack of emphasis on human abilities and the capacity to understand data. Data visualization has the ability to make abstract data comprehension simpler while also enhancing human talents. It alters the ratio between human cognition and allows the brain to use its maximum potential. Hidden meanings may be exposed when

complicated data is appropriately displayed. But it's important to make information visualizations in a way that fits human perception and works within its limits, since people may get overwhelmed by the amount of information given.

As a result, being able to assess how effectively an information representation is created is critical. Objective usability measures, such as the effectiveness of an information visualization (can users achieve their goals? how quickly can such objectives be accomplished? Businesses and academics were concerned in the subjective experiences of people in order to suit their needs and desires. The user's choice will be influenced by the UX: a good information visualization should deliver a positive user experience. Visualization's value to the experience cannot be underestimated. Aesthetics and simplicity of use are additional factors that usability research occasionally ignores. Few research work has been done about how to measure the experiences of data visualization, which is now the focus of data visualization evaluation.

1.1 Objectives and research queries

Several UX models are evaluated and their usefulness in the area of data visualization is assessed in a literature review on UX and data visualization. The characteristics of the ux (CUE) framework were identified as a good contender since it encompasses the most significant features of data visualization and allows for domain-specific customisation. This exploratory study will use an experiment to see whether the CUE model and associated measurement metrics are adequate for quantitatively assessing the UX of informational visualizations, even if the variations between the scenarios are minor. The numeric data was compared to the user's preferences and a qualitative UX evaluation. Animations in information visualizations will be the focus of this investigation since they may be both aesthetically pleasing and functionally useful. A variety of animations are tested to evaluate whether and how they affect the ux of a job engagement with an information presentation. To show what the extra benefit of the quantitative method is, the same animations will be evaluated using qualitative research.[1]

In this experiment, the non-instrumental but also technical qualities of a visualization were both affected by animations, therefore they were treated as separate factors. In this experiment, two styles of graphics will be employed. To begin,

reload animations will be used since they have the most effect on the visualization's aesthetic aspects. The implementation of information systems processes is represented by the movement that occurs whenever a graph gets loaded, known as loading motions. Bartram's taxonomic of movement application areas' function description 'application area is linked to these animations. Amcharts and Highcharts are the two most commonly used loading animations in the d3 frameworks. Transition animations will also be used to adjust the visualization's instrumental but also non-instrumental quality. Two animations proposed by Heer and Robertson would be used to help participants better understand the link between a "layered bar graph" and a "grouped bar graph" while switching from one to the other.

As broad ideas, context, systems, and people all have an influence on the user experience, it is important to describe and scope them. Task-driven interactions with visualizations will be the focus of this research. In this scenario, the UX is heavily influenced by both hedonic and pragmatic factors. Considering the screen upon which the visualisation will be exhibited is an additional contextual consideration. This study can run solely on a computer monitor for consistency's sake. Hence, animation will be the only component that affects the user's experience; hence the visuals will only change in terms of animation. When it comes to data, it's important to keep things consistent so that it doesn't interfere with the user's perception of what they're seeing. Other characteristics, such as the visualization's color, will remain consistent across all settings. In terms of users, this study is aimed at inexperienced users who are seeing the representation for the first time and have a desire for knowledge, which is, in this instance, induced by the experiment's tasks. Even if their emotional condition effects the UX, it is beyond the scope of this study. Because this study aims to draw generalizable results for any sort of user with an information requirement, the level of familiarity with information visualizations among users will not be stated or explored. Bar charts, stacked bar graphs, and grouped bar graphs are used to avoid overrating the capabilities of human vision and to respect the limitations.

Research questions

For this reason, a literature research was conducted in order to assess models as well as definitions of user experience (UX) in order to apply them to data visualization. Data visualization has also been explored in more detail in order

to uncover UX concepts that relate well to the area of data visualization. As a starting point, let's consider the following question::

RQ1 – What metrics may be used to measure the effectiveness of a data visualization?

RQ1.1 – What are the definitions and models for user experience (UX)?

RQ1.2 – When it comes to data visualization, what are the most effective user experience models?

A literature study revealed that the CUE model, as well as the measurement meCUE, were viable options for quantifying user experience. As a result, the second question is:

RQ2 – Can the CUE model and associated measuring instrument, meCUE, be applied to the field of information visualization?

RQ2.1 – How may the CUE paradigm and its measuring tool meCUE be used to quantify variations in UX, and what does this have to do with evaluating the user experience (UX)?

RQ2.2 – Can the results of the meCUE survey structures be used to justify a visualization preference?

The CUE model as well as the meCUE survey were used to assess the UX of several variants with the same visualization in order to answer these questions. In terms of motions, the visualization diverged since animations might have both instrumental and non-instrumental meaning. Other techniques of UX evaluation were reviewed in addition to the meCUE findings. To translate the quantitative UX evaluation to a qualitative version, qualitative input about the circumstances was acquired. After analyzing and discussing the variations in the situations, a questionnaire was given. The research questions for this study will lead the answers to the questions above:

RQ3 - What effect do loading and transitions animations have on information visualizations' user experience?

RQ3.1 – In a goal-driven engagement with a data visualization, how does bouncy attempt to load visuals in a bar chart compare to the identical graphic display without animation?

RQ3.2 – If a loading animation is used, how does the user experience of a visualization differ from that of an identical display without the need for a loading

animation?

RQ3.3 – How does a from that animation work? How does the UX of a goal-driven action with a visual analytics with transition animation compare to the same visual without transition animation?

RQ3.4 – Is there a difference in UX between a pre-planned transformation movie (with two animation steps, the first of which keeps changing the nightclub's width and x-coordinates) and a picture that looks the same but doesn't have any transformation animation when the main goal is to communicate?

Although some participants may find the bouncing loading animation beautiful and trendy, it may be seen as disturbing. Both the transition animations are designed to improve the UX by helping participants comprehend the relationship between the two representations of the graph. Furthermore, the transitions may improve the aesthetic quality of the impression. The graphics are likely to promote participation in any situation. Because the differences here between animation and movement are so slight, the disparities between the animations are likely to be bigger. Visualizations that are seen to have a greater aesthetic quality may also be thought to be more useable and beneficial. This would confirm Tractinsky et al.'s that "what is attractive is useful." [8] Even if the differences between the circumstances are minor, the findings of the meCUE measures are expected to show significant disparities in the majority of cases. There may be no discernible change between situations that are quite similar, such as the two transition animations. The CUE model says that changes in different parts of the meCUE data between conditions should explain why a participant chose a certain condition.

1.2 Thesis Outline

This article is organized into six sections: the first, Introduction, provides a short summary of data visualization throughout the globe as well as research issues. The second component discusses data visualization and user experience. The third and fourth parts discuss experimental procedures and findings. The fifth part includes a description of development, logical structure, and outcomes. In the last chapter, we reach our findings.

2. Data visualization user experience evaluation

2.1 Data visualization

Since the digital era, when more data became accessible, the area called data visualization has grown in popularity. Even while the tabular form was originally employed in the second century to store astronomical data, it was much later, during the 17th century, that the numerical method was shown in two-dimensional graphs. The graphs we know today were devised or refined after that, in the early 18th and 19th centuries. William Playfair, for example, created the graph and the bar graphs. Universities began to acknowledge the topic of data graphing in the 19th century. In 1977, statistics prof. Tukey realized the value of visualization and launched exploratory data analysis, a novel technique for data analysis. A few years later, Tufte published the seminal "The Visual Presentation of Quantitative Information," which demonstrated excellent data visualization techniques.

We have a lot of information at our disposal because we live in a culture that is increasingly reliant on data-intensive technology. The enormous number demonstrates its potential, but the issue of how we should investigate it arises often. Much attention is paid to technological advancements, such as the ability to collect, store, and retrieve information. Human talents for interpreting the data, which are essential to gain a deep understanding in the data, are not given enough attention. Since there are several tools for exploring and visualizing data, the outcomes are dependent on how well individuals use them. Good data analysis, according to Few, will enable us to:

- To have a better understanding of the current situation
- To better forecast what will probable happen in the future under certain

circumstances, so that opportunities and problems may be avoided.

Dashboards are a common kind of information visualization. A dashboard, according to Few, is a visual representation of the most relevant information required to accomplish one or more goals, which is condensed and presented in a smaller window so that the data can be seen at a glance. Dashboards often offer information from several viewpoints, as well as the relationships between them.

2.1.1 Data, knowledge, and information

The terms "data," "information," and "expertise" are often employed in visualization to denote differing levels of abstraction, understanding, or truth. There are instances when the phrases "data visualization" and "visual analytics" are used interchangeably to describe data communication tactics by coding them all in to visual objects. DIKW is a common paradigm for human comprehension in cognitive and sensory space, and it illustrates the difference between data and information. (Figure 2.1). Ackoff's first hypothesis was that

- Data is made up of unprocessed symbols;
- Information is information that has been given meaning and can answer questions like "who, what, where, and when."
- How questions are answered and information is placed into perspective are the hallmarks of knowledge, according to this definition.
- Awareness is the capacity to comprehend information while being cohesive and actionable.

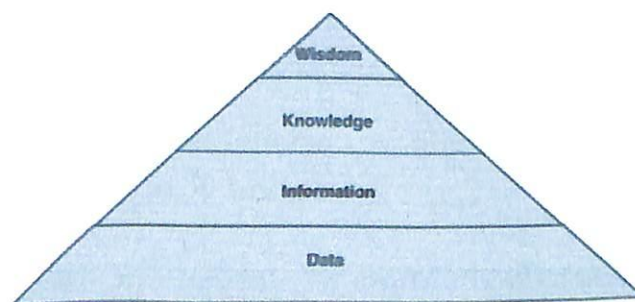


Figure 2.1: Human perception and cognition often follow the DIKW hierarchy (data-information-knowledge-wisdom), which describes the difference between data and information.

Few use the phrase "data visualization" to refer to the collection, display, and interpretation of data for the purpose of informing decision-making. Information

visualization is a particular kind of graphical representation. According to Card et al., "The use of computer-aided, interactive, graphical representations of abstract material to augment cognition" These computer-based and dynamic visualizations are more like games than infographics, which are mostly just pictures that don't change.

2.1.2 Data interpretation

Visual representations aid in the comprehension and exploration of facts. They are widely accessible, unlike advanced data methods, which is normally reserved for skilled professionals. "One important advantage of excellent pictorial representation," Tukey and Wilk write, "is that it may assist to express clearly and accurately a message delivered by numbers whose computation or inspection is far from simple." Visual representations, according to Few, let us perceive more at once and recall the content better. Comparing the graphical presentation in Figure 2.2 demonstrates this. The graph shows trends and peaks right away, but you have to look at the table for a long time to see the same things.

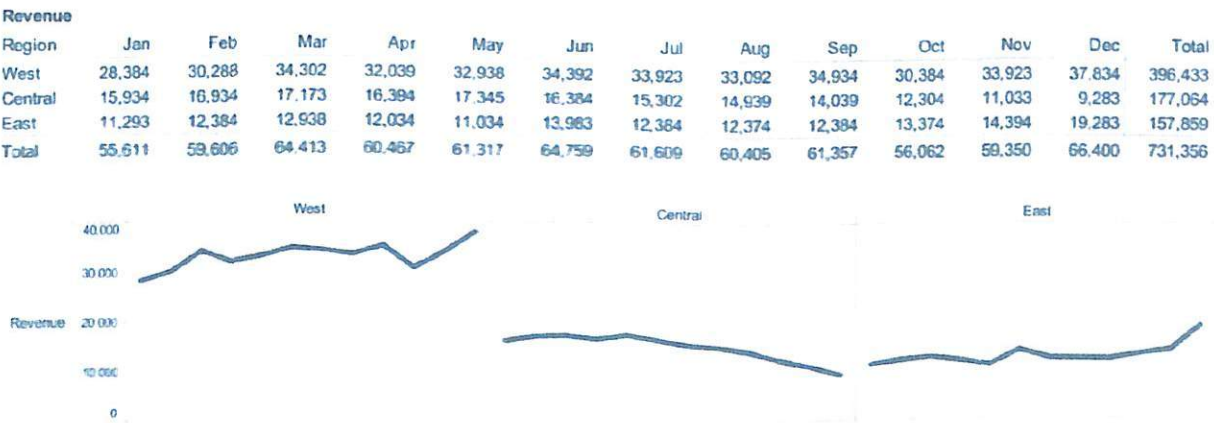


Figure 2.2: Tables versus graphs, where visualizations allow us to perceive more information at once and retain it better

Visual representations are useful for highlighting certain parts of data and creating a narrative, so deciding what to express is critical. Depending on the quantity and primary keys of the data, the same data might convey several distinct tales. A specific value might show growth over time as well as a value by area. There are several factors that go into making a good visualization: what information the audience needs, how they process visuals, and how they want the information presented. It's vital to know your users and their skill level before

designing any user interface. There have been attempts to define and build up frameworks for the literacy of data visualization. These frameworks may be used to determine the degree of expertise and design of data visualizations.

Choosing the proper form of visualization for the project is crucial since various types of visualizations are used for different purposes. There are a wide variety of visualizations to choose from at <https://datavizcatalogue.com>. A basic depiction, such a line or a chart, may have a wide range of different uses. As a common tool for tracking changes over time, line charts may be especially useful when comparing several variables. The message may be lost if it is used improperly. Both 2.3 and 2.4 illustrate this point well. While the figures in Figures 2.3 and 2.4 seem to be in agreement with the facts, the figures in Figure 2.4 appear to be less clear or even bizarre.

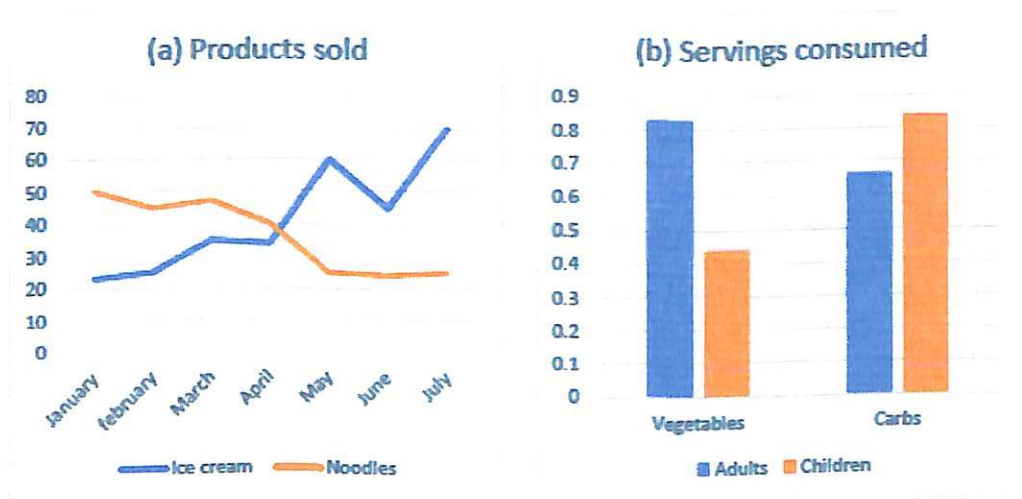


Figure 2.3: Line and bar charts that match the data's structure (graphs created in excel)

There is a fine line between strong focus visualization and "misleading" visualization. When someone is excessively anxious to communicate a specific message while leaving out vital information, or when someone is uninformed and does not employ norms, visualizations may be deceptive. Data visualization is similar to storytelling in that it allows someone to freely communicate their perception of a dataset. A single dataset may be interpreted in a variety of ways, telling many distinct tales. It is thus beneficial to be informed of typical methods for "lying with statistics," some of which are given below.

An example of this is the "misleading" shortening of the Y axis, which is common. It occurs when the y-axis is tampered with by graph designers who

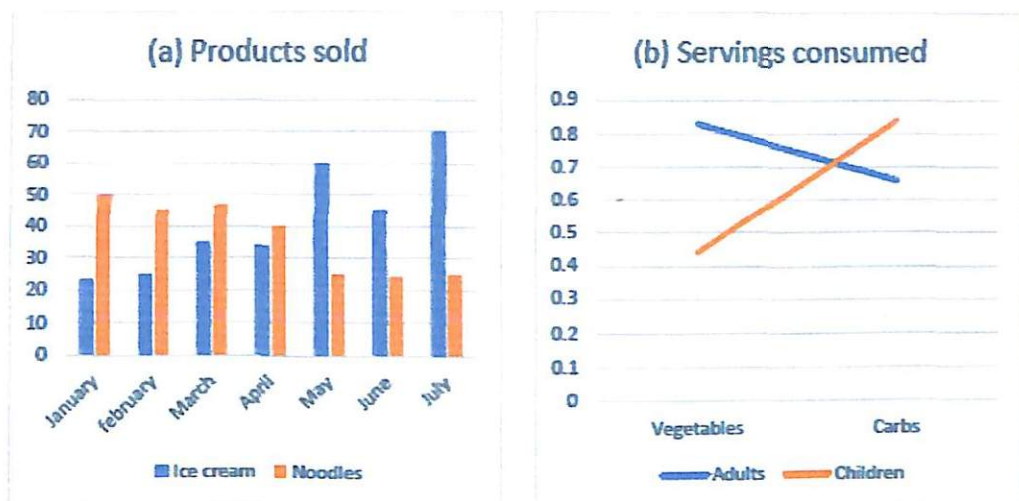


Figure 2.4: Due to a mismatch between the kind of data represented in the bar chart and the line chart, the results are confusing. Line and bar charts that match the data's structure (graphs created in excel)

don't follow convention. It is common for the y-axis to begin at zero and end at the highest point in the data set. However, the y-axis might be reduced to indicate a very minor difference. Figures 2.5 a and b demonstrate an instance of this phenomenon, where the rise in one figure seems to be rather considerable, yet the real increase in figure b is nearly undetectable. That the bottom line is wider than other lines in this situation, implying that it is zero.

Omitting data is just another method that might be deceptive; by omitting particular data points, patterns that may or may not exist can emerge. If data is ignored, there is a risk of omitting important information. It's possible to see trends that aren't obvious in the original data set, as seen in Figure 2.6a and b. Cropping the X and Y axis, or both, is another approach to deceiving with a graphic. Normally, this is merely a completely acceptable method of focusing in on the facts while excluding unneeded background. The goal should not, however, be to create a tale greater than what it already is. To making a trend seem better than it is, data might be altered to exclude a single increase.

The problem of correlation vs. causality is a last example. Causation is not implied by correlation. Nonetheless, a correlation is sometimes mistaken for causation, as seen by headlines like "People who drink beer live longer; having a beer is beneficial!" on the internet.

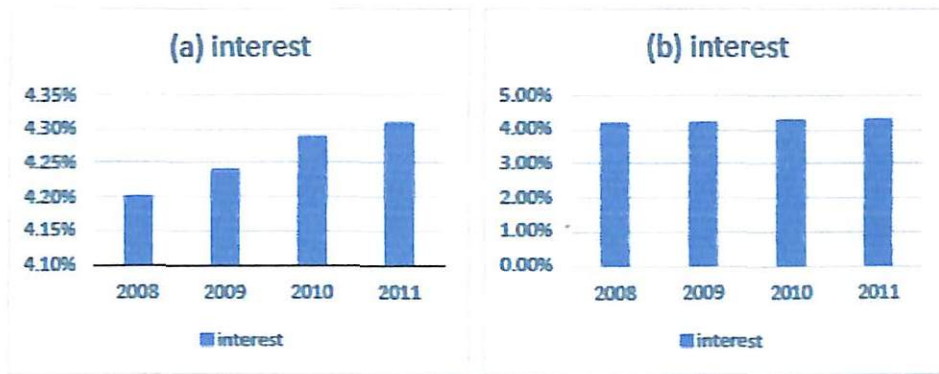


Figure 2.5: Sample of a truncated y-axis, where the rise in interest in (a) also is significant, while the real increase in (b) is hardly perceptible.

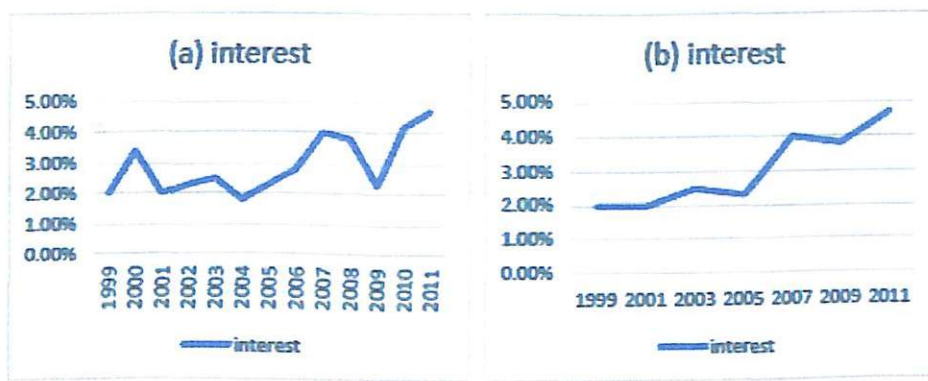


Figure 2.6: Example of missing data: (a) displays the original source of data, while (b) displays half of (a), resulting in a trend that is not visible in (a)

2.1.3 Visual encodings and human perception

Technology has advanced at a breakneck pace, while human evolution has lagged behind. As a result, it's critical to create information representations that take into account human perception abilities while also acknowledging their limits. Bertin claimed that visual perception follows a set of principles that may be followed to perceive information clearly. Pre-attentively, he says, the brain perceives a wide range of basic visual properties. Ware highlights the significance of using aspects of pre-attentiveness when depicting abstract information graphically. He asserts that some fundamental shapes and colors stick out and may be noticed visually even after a brief exposure.

Few state the following truths concerning perceptual knowledge:

- We don't pay attention to everything we see since being aware of all that we see would be overwhelming. So, in visualizations, we should try to make sure

that important information stands out from other data that isn't as important.

- We are attracted to patterns we are acquainted with; we just saw what we anticipated. As a result, information visualization should be based on knowledge of how people think.

- Working memory is critical to human cognition, yet it is severely constrained. We only recall the aspects that we were present for. As a result, information visualizations should be used as a supplement to working memory.

Perception-based criteria may be used to display data in such a way that the relevant and useful patterns emerge. In order to make abstract data understandable, it must be presented in a way that is visible and meaningful. In Figure 2.3, Ware provided a list of the most essential pre-attentive features that are most advantageous in information visualization, as shown.

2.3 shows how height and 2D location are seen quite precisely, but breadth, size, intensity, and blur are not, as shown in Figure 2.3. As a result, the majority of graphs employ these 2D orientation and length characteristics. In a Stanford University study, Figures 2.4 and 2.5 show the effectiveness of visual decoding and the predicted error rates for different encoding schemes. These figures show the different types of orientation encoding that were tested and show that people can estimate lengths more accurately when the objects to compare are closer together. Given how different the predicted errors are for angles and areas, it's not surprising that pie charts, which compare areas and angles, are often criticized as a way to show information.

2.1.4 Gestalt perception rules

Psychology is the study of how people get and keep their ideas in a world that seems chaotic. The core premise is that resources should be accessed as a whole rather than as a set of parts. The use of gestalt concepts in the creation of information visualizations improves their understandability. For example, Lemon, Allen, Carver, and Bradshaw show how the gestalt principles of similarity, closeness, and continuity affect how diagrams are understood, and Rusu show how the gestalt concept of closure may make graphs easier to read.

The notions of emergence, reification, multi-stability, and invariance are central to gestalt psychology. The emergence principle describes the mechanism through which people frequently recognize the whole before the components. The

Group	Attribute		
Form	Length	Width	Orientation
			
	Size	Shape	Curvature
Color			
	Enclosure	Blur	
			
Spatial Position	Hue	Intensity	
			
Motion	2-D Position	Spatial Grouping	
			
	Direction		
			

Figure 2.7: Pre-attentive visual perceptual characteristics that are most beneficial in data visualisation for encoding

reification principle is concerned with the element of vision in which things are believed to contain more spatial features than what is really available; human perception appears to fill in gaps. The idea of "multi-stability" describes how ambiguous sensory experiences tend to switch between different meanings in order to get rid of visual ambiguity, even though you can't see both meanings at the same time. The idea of invariance describes how similar and different things can be told apart no matter how big or small they are or how they are turned or moved.

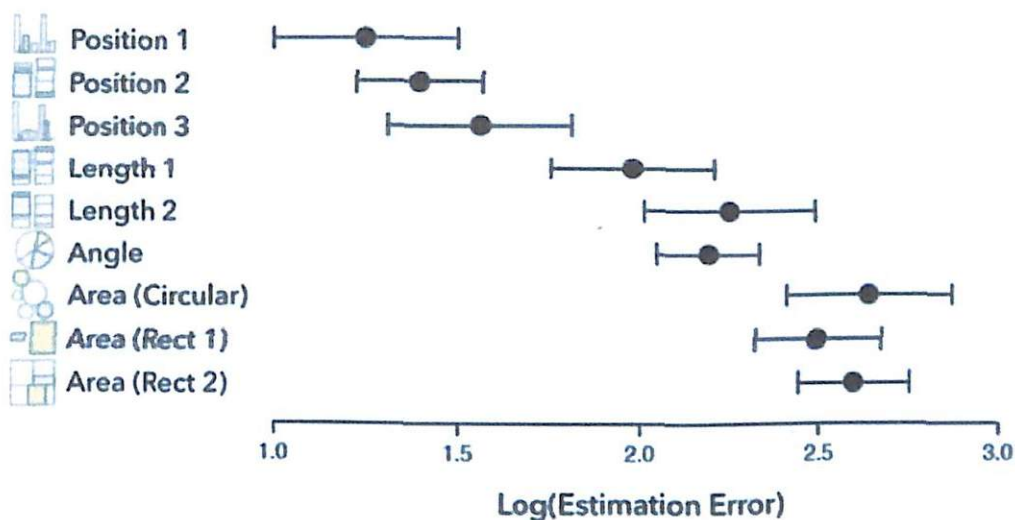


Figure 2.8: The efficiency of visual decoding; findings from a Stanford University study comparing visual decoding accuracy to predicted error rates for various encoding methods.

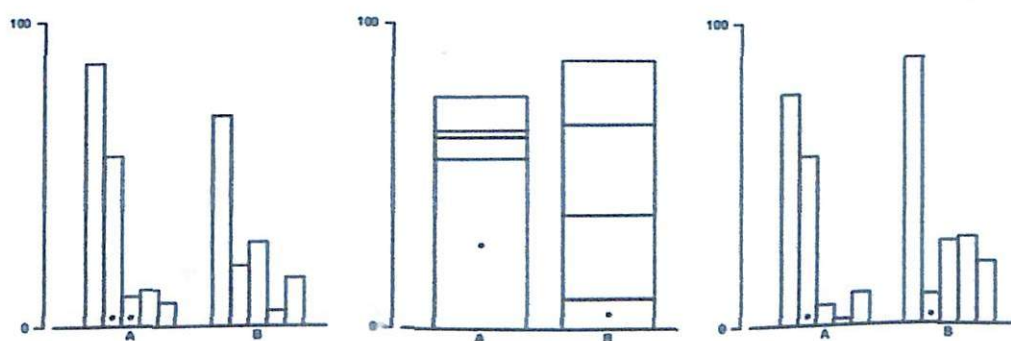


Figure 2.9: The various types of orientation that were assessed, demonstrating that when the things to be compared are closer together, people can more exactly estimate length. From top to bottom: Figure 2.4: position 1,2,3

2.1.5 Discussion

Data visualization may improve data accessibility by extending the user set of information beyond merely qualified experts. Data visualization, as defined by Few, is an umbrella word for all activities that involve communication, visual presentation, and analysis of data with the goal of making better decisions. The major focus of this thesis is information visualization, which is a kind of graphical representation. A decent visualization of data should match and respect the capabilities of human vision. As a result, it is also critical to have a thorough understanding of the target population, including user demands and characteristics.

This allows for better decisions about how a narrative should be delivered and which graphics should be utilized. As a result, Few's pre-attentive characteristics list and gestalt psychology's principles may help us select graphs that are more effective in conveying information.

2.2 User experience

User Experience (UX) has several different definitions depending on the profession and the expert. Usability, attractiveness, hedonic, effective, and experiential characteristics of technology usage are among the meanings. On the [allaboutUX](#) website, there is a collection of definitions. UX encompasses a wide range of academic topics, and each field has its own perspective on the subject. The numerous definitions appear to agree that UX is really about the interaction experience. Some versions have a commercial viewpoint and a marketing-oriented focus^{2,3}, whilst others are only concerned with the user experience of interactive goods and are HCI focused.

UX has increased in prominence in recent years, mostly as a reaction to the prevalent "usability" paradigm, which is task-based and work-related. Users' experience (UX) is a direct result of the product's usability, according to industry standards (ISO 9241-11, 2017). It's considered that usability is a product that affects the user's experience. It is thus possible to apply usability criteria to examine UX components, but UX also comprises other important features that research ignores, such as aesthetic appeal and feelings and experiences, that have been discovered to play a part in explaining why people prefer some methods over others. Keeping in mind that UX is not something that can be designed, but rather something that can be built for, it is important to note. The experience will always be influenced by the setting and the user. A first-time user may have a very unique dynamic compared to a tenth-time user, implying that the UX changes through time.

There wasn't a broad acceptance of what "UX" meant, so the phrase was used as a buzzword for a number of tasks that didn't fully fit into the accessible paradigm. Usability, user interface (UI), conversation experience (CE), systems engineering (SE), customer experience (CE), quality web attract (QWE), emotion (E), and the "wow effect" (WOW) are all terms that may be used interchangeably

when discussing UX, according to Roto, Law, and Vermeeren's UX whitepaper. Aside from being tied to UX, these terms have other meanings.

Data visualization seems to fit under a variety of UX definitions. UX was defined in 1996 by Alben, who gave a broad definition that is still widely used today:

Every aspect of a person's engagement with a data system is taken into consideration, from how they feel when holding it, to how they perceive its operation, to how they respond to it while using it. It is also important to think about whether or not the product matches their requirements and whether or not it is appropriate for the setting in which they want to utilize it.

Hassenzahl defined UX in terms of three primary factors: the user's condition, design attributes, and context. He also shows how UX is connected to usability in his definition, defining usability as a system property. Hassenzahl defined user experience as:

There are several variables that influence how well an association works, including the qualities of the planned system (such as its level of complexity or usefulness or functionality), the user's internal state, and the environment in which the association takes place (organizational outcomes setting, task significance of the activity, informed consent of use, etc.).

By contrast, Roto argues that UX is a subjective emotional response to a product, and one that many descriptions fail to include. The International Organization for Standardization (ISO) attempted to provide a definition for User Experience. UX is defined by the ISO as:

The user's reactions and perceptions as a consequence of using or anticipating using a system, product, or resource (ISO 9241-11, 2017).

According to ISO, these impressions have taken into account the user's emotions and physical and psychological reactions that occur before, during, and after use. The ISO definition, as per Law et al., is highly promising, although several terms will need more explication.

As stated by Hassenzahl,⁴ the user's interior life, the platforms, and the setting all have a 'role in these consumers' views and responses,' hence the ISO definition will be used in this thesis.

2.2.1 Methods of UX assessment

Roto et al. looked at UX assessment approaches and identified five different types: lab research, field research, surveys, expert evaluation, and blended methodologies.

Lab investigations are particularly useful for prototype assessment in the early stages. Participants are given a task to complete using one or more user interfaces. "Think aloud" is a popular technique. The analyst watches the person and tries to figure out what mental models they have. This is comparable to a usability test, except it additionally considers the user's experience. Field studies are typically useful and encouraged since they look at actual settings, which are critical to UX. People are watched and questioned during prototype testing in field studies. Surveys may offer input in a short amount of time and are simple to conduct on a broad, worldwide basis. It's usual to have an appropriate review of a design at the early prototype phase. Expert assessments performed prior to the user research may help you avoid wasting money on a costly user study.

It's also difficult since there are no pre-defined heuristics in UX. Using point of view inspection in the assessment to allow experts to concentrate on one particular experience feature is one technique to conduct an expert evaluation. Mixed approaches are often employed since it is vital to acquire richer data in many ways. Observing followed by interviews are two examples. Because it is difficult to discern subjective sentiments from a single observation, observations should generally be combined with other data-gathering approaches. "A word of caution when evaluating these results, which are based on the views of user experience assessors rather than hard facts," Mao et al. warn.[3]

Psycho-physiological measures are an objective way to assess user experience. Heart rate, skin sweat, and facial muscles are just a few examples. Facial muscles, in particular, are a potential arena for measuring positive and negative emotions. Psychological measures have the benefit of allowing the researcher to assess instant sensations without interfering with the user's involvement. On the other hand, existing technology still necessitates the use of intrusive measuring equipment, which affects the user's experience and increases the cost of study. Furthermore, only a few areas value immediate feelings.

2.2.2 Models of user experience

The many perspectives on UX, and also the term's broad definition, result in a wide range of opinions on the subject. Different assessment approaches concentrate on different elements of the user experience: They include anything from psychological needs analysis to task-oriented user objectives and guidance. A divide between academics and practice, partially driven by a lack of publicly accessible, consistent assessment techniques, contributes to this variation. In fact, UX assessments are often still dependent on usability methodologies since R and D teams have typically concentrated on usability while marketing departments have been responsible for communicating a certain experience. A change in assessment methodology should accompany a shift in perspective on product interactions from usability to experience.

Hassenzahl's user experience model

Roto et al. (2011) elaborates on this concept more (2011). Among other things, the user state refers to a person's desire to utilize a certain product, as well as their expectations and previous experience with the product. Among the many factors that go into determining how well a product is received by customers is their impression of the brand's overall aesthetics, usefulness, and functionality. Many factors impact context, including social context, physical, task, and technological and informational background.

Hedonic and pragmatic traits are further distinguished in Hassenzahl's model of UX (Hassenzahl et al., 2000), with pragmatic features aiding in achieving hedonic aims. Hedonic and pragmatic product attributes are described by Hassenzahl (2003) as follows:

In addition to classic usability metrics like learnability, efficiency, and effectiveness, there are pragmatic attributes that are closely linked to these metrics.

useful functionality (utility) and mechanisms to evaluate this utility are necessary for manipulating the environment (usability)

It is the non-instrumental parts that the user enjoys that are called hedonic. As an example, consider features that entice customers based on how they perceive the product, how they behave, or how they think about it.

Encouragement of skill development and the spread of information.. Attempt-

ing to provide the user with new insights and surprises, for example, by providing an unexpected but yet welcome tip.

The product must be able to transmit identification, since people express themselves via tangible items. • Identification. Personal homepages, which may be used to show oneself to others, are a form of identity. Sometimes the possession is designed to convey a favorable image.

- Evocation, the ability of a product to elicit memories in users. In addition, prior encounters with items have an impact on how a person views the new product.

A clear separation is made between objective quality factors and user perceptions of these qualities, as outlined by Hassenzahl. In addition to objective features, the user's traits and the context in which the product is used can influence the perceived quality. In the end, these perceived traits lead to a judgment of appeal. UX should be addressed as a dynamic and subjective idea, rather than as a one-size-fits-all paradigm, according to Hassenzahl (Hassenzahl, 2008b). This paradigm sees usability measurements as product characteristics.

Model for the components of the user experience

There is a similarity between Mahlke and Thüring (2007)'s Elements of Ux (CUE) model and Hassenzahl's approach. Pragmatic and hedonic aspects may be compared towards the model's instrumental but also non-instrumental properties, which are likely to influence the user's emotional response. Users' traits, as well as the system's attributes and the context/task, have an influence on the UX of an encounter. Research has shown that interaction traits may directly influence emotions, and that they are not just influenced by the product's quality attributes alone (Aranyi van Schaik, 2016) .

In a research based on the CUE model, Mahlke showed that there was no link between instrumental and non-instrumental qualities. They used a selection of the SUMI survey to measure the usability (instrumental qualities) and the classical aesthetics questionnaire to measure the aesthetic (the non-instrumental qualities) for this validation study. Classical aesthetics and expressive aesthetics are distinguished in this questionnaire. Examples of classical aesthetics include order and clarity in design. The potential of a design to defy expectations is at the heart of expressive aesthetics. In contrast, Hassenzahl claims that this ques-

tionnaire's expressive component measures more symbolic or motivating elements of an interactive product's visual attributes than it does obviously aesthetically aspects. After each task, the SAM survey and physical data, such as heart rate, were used to gauge the emotional response of the user. Individuals were asked to rate the systems according to their own preferences. In this investigation, the physiological assessments were not very accurate or important.

An attempt to standardize UX assessment was made with the development of the meCUE ('modular evaluation of user experience') questionnaire.

Three distinct modules were built and tested for this review.

Product attributes (both instrumental and non-instrumental) comprise the first module, user emotion constitutes the second, and repercussions resulting from user experience constitute the last module.

This model's modularity allows researchers to tailor the meCUE assessment approach to individual research objectives by selecting the necessary elements.

Model of Honeycomb User Experience

The User experience Honeycomb Model is a well-known approach to user experience design. Rather of focusing just on usability, this approach was designed to assist individuals realize the importance of prioritizing their design goals. It is the combination of these six aspects that determines the value of a product to its user, and that balance is determined by the context, content, and the people who use it. The honeycomb model for user experience (UX) is seldom addressed or utilized in scholarly literature, but it is often used in practice since it communicates the idea in a clear and concise manner.

The honeycomb paradigm has been used to data visualization. At the very least, an information visualization must be useable, attractive, believable, aesthetically acceptable and technically suitable in order to be a success on the user experience level.

2.2.3 Contextual factors

UX models are often used to assist designers in refining their concepts and products by examining how end users interact with various aspects of the system. UX is a highly subjective, dynamic, and context-dependent area, hence contextual im-

pacts are critical to grasp. The system, the users, the context, and the temporal aspects are the four key areas of UX impacts, according to studies. Users, context, and time will all be addressed in this section, which builds on the previous models' attention to system impacts.

The user

Human-Computer Interaction (HCI) has shifted its focus from focusing on what computer can do to focusing on what humans can do, stressing the need of knowing the user. Beginners, intermediate users, and advanced users may all be grouped together. An individual user's cognitive, behavioral, and socioeconomic characteristics, as well as his or her demographics, determine the level of expertise he or she attains in the application. Previous experiences with the substance have an effect on these abilities.

Context

The actual environment or place where the system is utilized, as well as the circumstances in this environment, such as whether there is adequate light, decent internet, and so on, are referred to as the context. The social-economic context, this same market background, this same historic context, and the use context can all be considered.[1]

Aspects of moment

When it comes to the user's experience, timing is everything. Animations might be attractive at first, but if they're used often, they can become a nuisance and take up too much of one's time. It has been shown by Wilamowitz-Moellendorff et al. that pragmatic quality (primarily usability) gains in value with time whereas hedonic quality loses its significance. Also discussed by Roto et al. is how changes in the UX over time have an effect on UX. Prior to their initial meeting with a system, people may have had indirect interactions with it because of expectations established by linked technology, brand, advertising and presentations or other people's thoughts on the system. This is important to keep in mind. What Roto and others call "anticipated UX" is what they're referring about here. It's also possible that after using a product, individuals may reflect on previous uses or modify their opinions about it, which is called episodic UX. To put it another way, "momentary UX" relates to how you feel when using a product. It's also worth noting that aggregate UX, which is the whole total of user

opinions over an extended period of usage, is identified by Roto and colleagues. Instead of concentrating on long-term use, a design and evaluation approach that prioritizes the momentary enjoyment of a product is more appropriate.[7] So far, most UX evaluations have been centered on short-term, instantaneous UX, such as analyzing the UX of that first interaction with a system. Only a few pieces of research have been published that concentrate on long-term UX. According to the research, timing is often overlooked, and having good experiences early in life is not as important for getting people to use something for a long time.

2.2.4 Discussion

Most UX frameworks incorporate usability as a direct influencing aspect, including metrics like efficiency, effectiveness, and satisfaction. UX is concerned with how people perceive their engagement, while usability is concerned with how easy it is to use and achieve objectives. So, it shouldn't be a surprise that all usability factors affect how the user sees the product, and most UX models make this clear.

The QUX paradigm, for example, sees UX as a total of specific characteristics at various interaction levels. The model includes 9 clearly measurable components, such as product-specific characteristics, ambient impacts, and even emotive user responses like contentment. As part of a thorough literature search and integrating characteristics that are often mentioned but not founded in a strong UX theory and framework, this model was developed. Although there are substantial variances, there are some parallels between the QUX and ISO factors.

It is common for other models to describe UX in terms of utilitarian and non-utilitarian attributes. Hassenzahl's UX model and the CUE model both explain how these two features affect emotional user responses, and this distinction is evident.[4] This difference may be connected to Morville's honeycomb model, in which utility, usability, findability, and believability are all important traits. Value and appeal, on the other hand, aren't necessary (Table 2.1). However, rather than being a product characteristic, desirability might be considered as an emotional consumer response. In contrast to other models, these three models emphasize how important context is to UX, but they don't explain how context affects UX in a clear way.

The honeycomb UX method concentrates on pragmatic aspects, while Hassenzahl's UX model focuses on hedonistic traits. Hassenzahl does point out that,

	Hassenzahl's User Experience Model	Model CUEe	UX Model Honeycomb
Hedonic / non-instrumental characteristics	Stimulation Identification Evocation	Aesthetic qualities Symbolic qualities Motivational qualities	Value (result of all factors) Desirability
Pragmatic / instrumental characteristics	Manipulation	Usability Usefulness	Usefulness Usability Findability Accessibility Credibility

Table 2.1: shows the pragmatic and hedonic features of the Hassenzahl UX design, Honeycomb UX model, and CUE paradigm.

although persona quality will ultimately lead to judgments of satisfaction and fulfillment, hedonics should not be allowed to eclipse pragmatic factors, which have also been demonstrated to have detrimental implications. All these instrumental and non-instrumental features are emphasized in the CUE model, which incorporates a considerable portion of what other models describe. Components are important in different contexts, according to all theories.[3]

2.3 UX evaluation of data visualization

It is possible to use Few’s data visualization effectiveness profile to examine key portions of UX models for information visualization, as defined in Few’s profile. Pragmatic and hedonic/non-instrumental components in various UX frameworks may be connected to the informational and emotional subtypes of these characteristics.

Interesting (product understanding)

- Usability: Meet the demands of the user; the info should be helpful.
- Completeness: the proper quantity and kind of information, as well as context for understanding
- Perceptibility: provide information in a way that a person can understand with minimum effort and accuracy.
- Objectivity: the information visualization’s validity, correctness, and precision.

- Intuitiveness: a visual analytics should be intuitive in the sense that it is basic and simple to comprehend. It is user-dependent.

Evocative

- Aesthetics: The visualisation must be visually appealing.
- Inviting the user to investigate the material is essential.

When evaluating UX in terms of hedonic and pragmatic features, Hassenzahl et al. say that the balance between these aspects is dependent on the mode of use. During "active mode," when the action is considerable and goals are generated on the fly, the attraction of websites is totally impacted by hedonic qualities. Goal mode is a location whereby the hedonic and pragmatic factors play an important part in behavior, where the goals impact. UX models must explicitly address usability metrics in this context since information visualizations are typically used in goal mode to satisfy a particular information need. When choosing a good UX model for information visualization, it's important to think about how websites and information visualizations are different.

The majority of information visualizations are based on pictures, but the majority of websites are text-based. To further emphasize the value of the material, websites typically provide qualitative data (such as videos or photographs) rather than relying just on their presentation. On the other hand, data visualization relies on the display of quantitative information. [2]

The UX paradigm must thus include visual components, in particular. It's clear that these other user experience models emphasize status and identity above the actual world. Since it is not something a person owns or is affiliated with, data visualization does not allow for identity or status. A few user experience theories have a stronger case for this assertion than others. Hedonistic features in data presentation are emphasized more in Hassenzahl's model and in the evaluation procedures that are built around it. A problem with this paradigm is that it seems to undervalue accessibility and usability, which are both equally important to the hedonic domain, and so does not cover all of the hedonic domain's aspects. Visual and aesthetic aspects are well-represented in the CUE model, which also gives significant weight to non-instrumental elements. A wide range of interpretations and applications may be drawn from the theory and its tools. While engagement is seldom mentioned as a necessary attribute of data visualization, it may be considered a "quasi-quality" of the medium. Because the assessment model is

made up of separate parts, extra items, even ones with special status, may not be included in the data visualization process.

3. Method

3.1 Participants

Suleyman Demirel University students and teachers participated in the survey. The sample was selected to be 18 years or older and younger than 65 to ensure that it includes individuals who have most likely come into contact with (digital) graphs. No further participation limits were imposed in order to make the research as generalizable as feasible. Participants were given chocolate if they answered all questions correctly, in order to encourage them to respond honestly and not simply click arbitrarily. The experiment was first undertaken with 50 people. Another 50 people completed the experiment after the UX questionnaire was changed to assess the meCUE construct 'emotions,' as stated in the 'measures.' Because people could only participate once, the experiment required a minimum of 120 volunteers. Because of the small number of variables across the scenarios, the result was expected to be minimal. Several data inclusion criteria were developed to assure the dependability of both crowdsourced internet data and crowdsourced internet data. Participants must have first viewed the animation. As a consequence, they should have switched between views. Because the questions are basic and can be inferred from the graphs, there should have been more than two valid answers for each task. This criteria allows for no more than one inaccurate answer in every three. A long enough time limit on the first UX questionnaire is necessary to weed out users who just clicked through the questions without providing any meaningful responses. Slattery and Yates' study showed that their fastest reader can read 246 words per minute while being right, hence the preceding completion time restrictions are based on their findings. Furthermore, it is expected that clicking the response just on the 7-point Likert scale would take probably half a second. Incomplete responses excluded four candidates, while the remaining 24

were rejected for the reasons listed below. More over two-thirds of the participants were weeded out (27 out of 100). One hundred and four people participated in all three types of questionnaires, resulting in an overall sample size of 74. Each round's participants' sexes are shown in Figure 3.1.

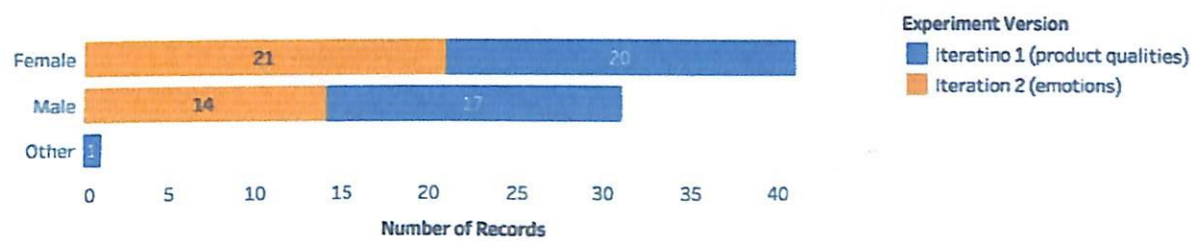


Figure 3.1: The gender distribution of experiment participants

Iteration 1's participant age characteristics are $M = 32$, $SD = 9.39$. Iteration 2's participant age characteristics are $M = 29$, $SD = 8.05$. General participant age characteristics : $M = 31$, $SD = 8.85$. (Figure 3.2)

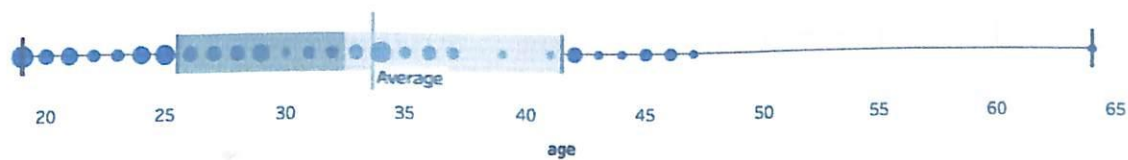


Figure 3.2: Age distribution of participants as a boxplot with the mean

3.2 Measures

The meCUE survey, based upon the CUE model, was used to quantify the user experience of the interaction between both users and graph. Because they are not well-suited to data visualization, variables such as emotions, status, devotion, intent to use, or brand trust were omitted from the first experiment. The term "status" does not apply to data visualization since it is not anything that a person owns or is associated with. Because the engagement in this research is goal-based, conceptions like "commitment," "intention to use," and "product loyalty" are less appropriate. Instead, these constructs depend on the goal as well as the experiment itself. Because the variations in the circumstances were thought to be too tiny to have a detectable influence on emotions, the notions of "emotions" (both pro and con) were left out. The first iteration uses the meCUE

Item
Age
Gender
Education level
Nationality
Employment status
Total time taken for the experiment
Date experiment
Answer speed per questionnaire
Number of clicks (switches between views) per condition
Correct answers per condition

questionnaire to obtain quantitative user experience data, while the second uses an open question to get qualitative data. Afterwards, the situations are evaluated against one another, and a more favorable state is demanded. When conducting an experiment, Prolific is used to gather information about participants and the experiment itself.

MeCUE survey module III was utilized instead of objective but also non-instrumental product qualities in a second iteration of this experiment to measure negative and positive feelings about the visuals. First and foremost, the emotional components of the meCUE survey were omitted since the circumstances were thought to have no influence on them and to shorten the questionnaire. However, based on the input from the initial iteration, it seems that certain settings do in fact elicit feelings. In a second version of the experiment, it was decided to quantify emotions. The qualitative UX questions were changed with the variables given below in this iteration, but the rest of the measurements remained the same.

3.3 Tasks

Participants have to perform activities in order to engage with the graph. Each visualization exercise consists of 3 multiple-choice questions. Low-level analytic activities that Amar et al. indicated were primarily concerned with seeing how individuals behave were used to build them.

Part 1 (the loading animation graphs):

- 1. Obtain a value

- 2. Operation of the filter
- 3. Locate the extreme.

Part 2 (graphics with animation transitions):

- 1. Locate the extreme.
- 2. Get two values and compare them
- 3. Recover the value

3.4 Procedure

The research is divided into two sections, each with three conditions. There is no animation in one of the situations for each section, while the other two components contain animation with a tiny variation between them. In a within-subjects study on their experience, the participants rated all six visualizations. As a result of its higher power and lower unpredictability, the within-design was chosen as the best design for subjective judgements. Within parts 1 and 2, Latin square random was used to address within-subject study issues such as attitude development, weariness, learning, and carryover effects. The research method is shown schematically in Figure 3.3.

The responder was asked a series of questions regarding his or her experiences with the vision immediately after each one. All 3 visualizations and UX questionnaires in part 1 were completed, so users were given a choice of which one they liked best. They were also asked whether they thought animation enhanced the graph or made it easier to understand. The individual might then go on to the next segment and repeat the procedure. Before the experiment is completed and the user is returned to Prolific, the participant gets the opportunity to provide additional comments after the second section. After that, the answer is examined, and if it is complete, the participant gets paid by Prolific.

The average time it took participants to finish the test was $953 \text{ s} = 15.8 \text{ m}$ (Figure 3.4). One outlier was omitted from this computation and graph, which was a person who had spent 178768 s ($= 50 \text{ h.}$) on the study. This user was unable to complete the experiment in one sitting.

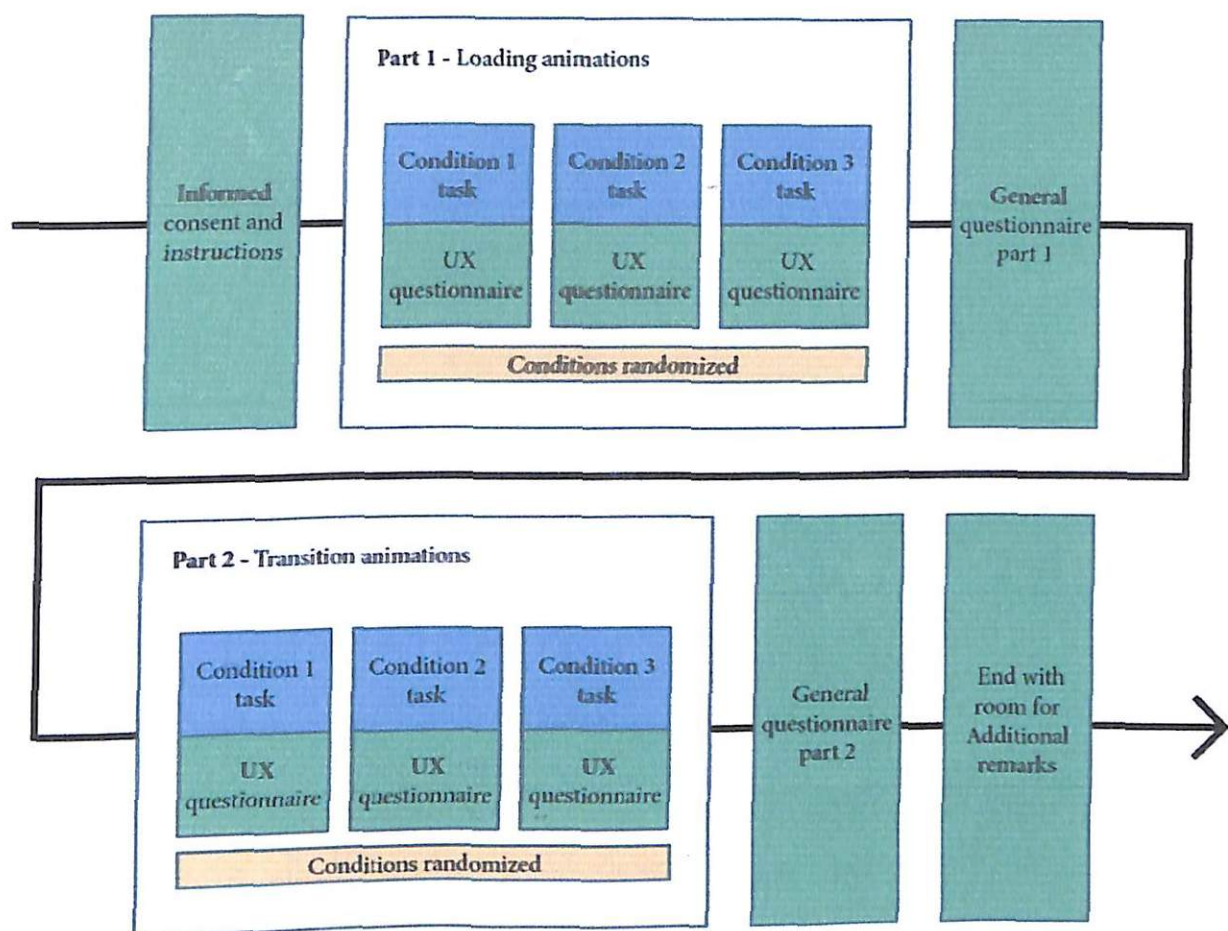


Figure 3.3: The research technique is shown in a diagram



Figure 3.4: Experiment participants' time spent on the experimen

3.5 Data analysis

Experiment participants' personal information is included in the data acquired throughout the experiment. Randomization group assignments and which visualizations participants found most appealing from each section. Task-specific information for all six activities was gathered for each participant, including objective interaction features and inner UX Likert values. Figure 3.5 depicts a schematic depiction of this data.

A test-retest approach, ANOVA, was used to assess meCUE data. Bonferroni-adjusted p-values

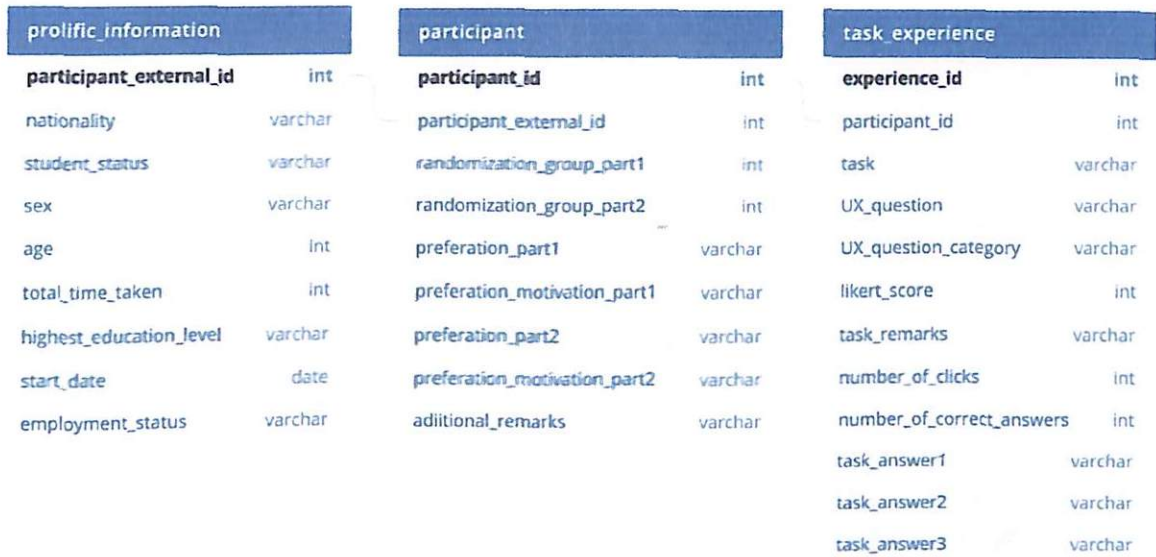


Figure 3.5: The information gathered throughout the experiment, as well as the relationships between the various components

The qualitative replies in the further remarks area were examined in more detail to discover what comments participants had on certain visualizations as well as how these comments varied by condition. The responses are scored on a scale of -2 (negative) to 2 (positive). The following are the definitions:

- -2 - Strongly negative words like "irritating," "awful," "stressful," and so on.
- -1 - A negative descriptor such as "a little off-putting," "I wasn't a huge fan of," and so on.
- 0 - Neutral remarks and positive and negative comments that balance others out are acceptable when discussing non-UX issues.
- 1 - Words like "easy to understand," "pleasant," and so on are all examples of positive adjectives.
- 2 - Overtly enthusiastic comments such as "I adore it," "I really like the animation," and so on.

Since the data compared two separate animations rather than three scenarios, one of which had no animation, paired-sample t-tests were used to examine the comparison questionnaire's results, which evaluated the animation after detailing the differences between the two conditions.

We looked at the chosen graphs for both sections to see if the differences in UX found in the meCUE survey could explain why this decision was made.

4. Results

4.1 meCUE questionnaire results

Divergent stacking bar graphs, an informative technique to illustrate Likert scales, are used to display the outcomes of the Quantitative approach (from 1-strongly disagree).

4.1.1 Product characteristics (n = 38) in meCUE iteration 1

The aesthetics, functionality, and usefulness of the product were evaluated in the initial iteration. The descriptive statistical analysis of the responses to the meCUE questionnaire's Likert scales on product attributes are shown in Figure 4.1.

			Mean	SD	N
Loading animations	Aesthetics	Bouncy Loading	5.28	1.45	19
		Calm Loading	5.37	1.35	19
		Static Loading	5.31	1.48	19
	Functionality	Bouncy Loading	6.46	0.98	19
		Calm Loading	6.65	0.84	19
		Static Loading	6.64	0.86	19
	Usability	Bouncy Loading	6.62	0.86	19
		Calm Loading	6.75	0.61	19
		Static Loading	6.70	0.61	19
Transition animations	Aesthetics	Direct Transition	5.38	1.59	19
		Staged Transition	5.35	1.76	19
		Static Transition	4.96	1.74	19
	Functionality	Direct Transition	5.83	1.50	19
		Staged Transition	5.56	1.60	19
		Static Transition	5.78	1.53	19
	Usability	Direct Transition	5.56	1.47	19
		Staged Transition	5.51	1.51	19
		Static Transition	5.62	1.45	19

Figure 4.1: Quality of product constructs of meCUE descriptive statistics

Animations for loading

There were no notable variations in aesthetics, usability, or functioning across the circumstances in iteration 1.

Aesthetics

The Huynh-Feldt value for the sphericity deviation was 0.882. The kind of loading animation has no effect on the overall aesthetics of the UX, according the meCUE findings, $F(1.764, 62.280) = .229, p = .768$. Figure 4.2 depicts these findings.

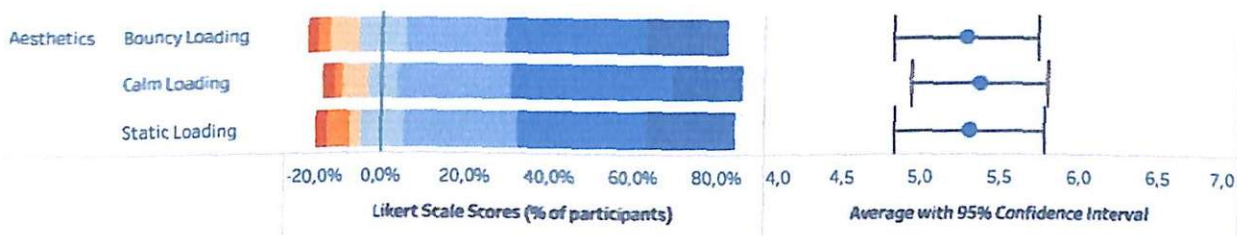


Figure 4.2: On the Likert Scale, ratings range between disagree (red) and agree totally (blue), with mean findings and 95 percent CIs on the left as well as average scores on the right..

Functionality

The Huynh-Feldt value for the sphericity deviation was 0.873. The kind of loading animation has no effect on the overall aesthetics of the UX, according the meCUE findings, $F(1.748, 64.665) = 2.752, p = .078$. Figure 4.3 depicts these findings.

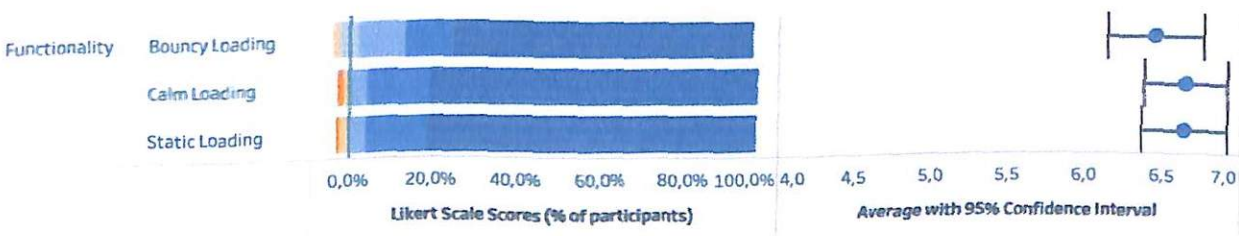


Figure 4.3: On the Likert Scale, ratings range between disagree (red) and agree totally (blue), with mean findings and 95 percent CIs on the left as well as average scores on the right.

Usability

The Huynh-Feldt value for the sphericity deviation was 0.853. The kind of loading animation has no effect on the overall aesthetics of the UX, according the meCUE findings, $F(1.706, 63.110) = 1.934, p = .159$. Figure 4.4 depicts these findings.

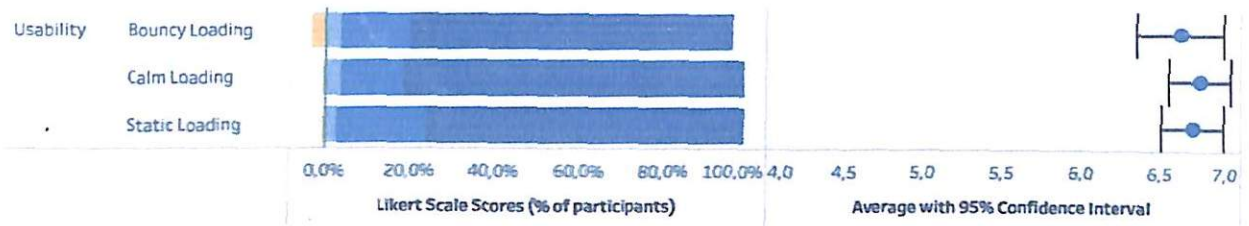


Figure 4.4: On the Likert Scale, ratings range between disagree (red) and agree totally (blue), with mean findings and 95 percent CIs on the left as well as average scores on the right

Transition animations

Aesthetics

The Huynh-Feldt value for the sphericity deviation was 0.795. The kind of loading animation has no effect on the overall aesthetics of the UX, according the meCUE findings, $F(1.590, 58.846) = 2.175, p = .133$. Figure 4.5 depicts these findings.

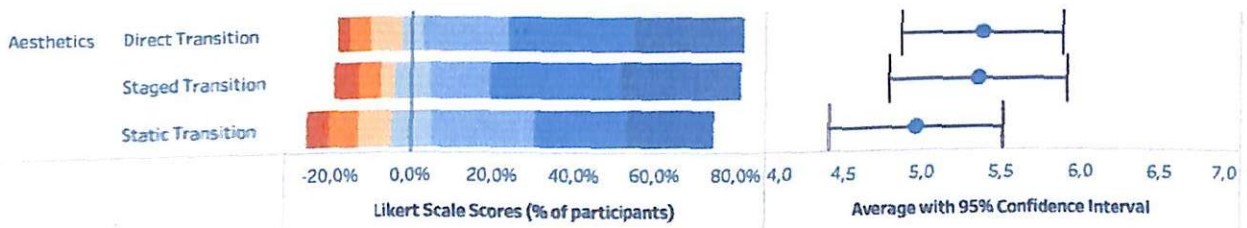


Figure 4.5: On the Likert Scale, ratings range between disagree (red) and agree totally (blue), with mean findings and 95 percent CIs on the left as well as average scores on the right.

Functionality

The Huynh-Feldt value for the sphericity deviation was 1. The kind of loading animation has no effect on the overall aesthetics of the UX, according the meCUE findings, $F(1.581, 47.604) = 1.229, p = .299$. Figure 4.6 depicts these findings.

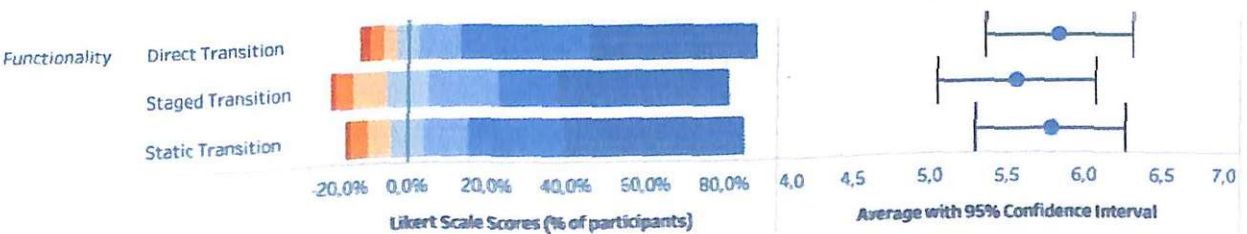


Figure 4.6: On the Likert Scale, ratings range between disagree (red) and agree totally (blue), with mean findings and 95 percent CIs on the left as well as average scores on the right.

Usability

The Huynh-Feldt value for the sphericity deviation was 0.973. The kind of loading animation has no effect on the overall aesthetics of the UX, according the meCUE findings, $F(1.946, 43.975) = .208, p = .807$. Figure 4.7 depicts these findings.

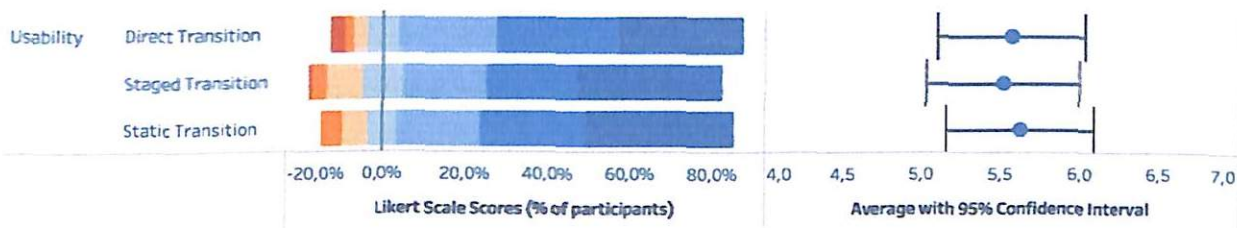


Figure 4.7: On the Likert Scale, ratings range between disagree (red) and agree totally (blue), with mean findings and 95 percent CIs on the left as well as average scores on the right.

4.1.2 Results from the second iteration of meCUE (n = 35)

Measurements of positive and negative sensations were made in the second installment of the experiment. Emotional statements are often opposed by a large majority of people. The descriptive statistical analysis of the responses to the meCUE questionnaire’s Likert scales on product attributes are shown in Figure 4.8.

			Mean	SD	N
Loading animations	Negative Emotions	Bouncy Loading	2.60	1.94	35
		Calm Loading	2.29	1.68	35
		Static Loading	2.13	1.52	35
	Positive Emotions	Bouncy Loading	2.71	1.60	35
		Calm Loading	2.92	1.56	35
		Static Loading	2.88	1.56	35
Transition animations	Negative Emotions	Direct Transition	2.65	1.52	35
		Staged Transition	2.80	1.79	35
		Static Transition	2.71	1.71	35
	Positive Emotions	Direct Transition	2.81	1.59	35
		Staged Transition	2.70	1.59	35
		Static Transition	2.54	1.42	35

Figure 4.8: The emotion components of meCUE have descriptive statistics.

Loading animations

For the positive and negative sentiments categories of the meCUE questionnaire, Figure 4.9 displays the average and 95 percent statistical models for the Likert-type scales.

Negative

The Greenhouse-Geisser estimation of sphericity deviation was 0.686. The kind of transition animation had no effect on the construct negative feelings of the UX, according to the meCUE data, $F(1.373, 46.079) = 2.977, p = .078$.

Positive

The Huynh-Feldt value for the sphericity deviation was 0.936. The kind of loading animation had no effect on the construct good feelings of the UX, according the meCUE findings, $F(1.872, 39.984) = .719, p = .477$.

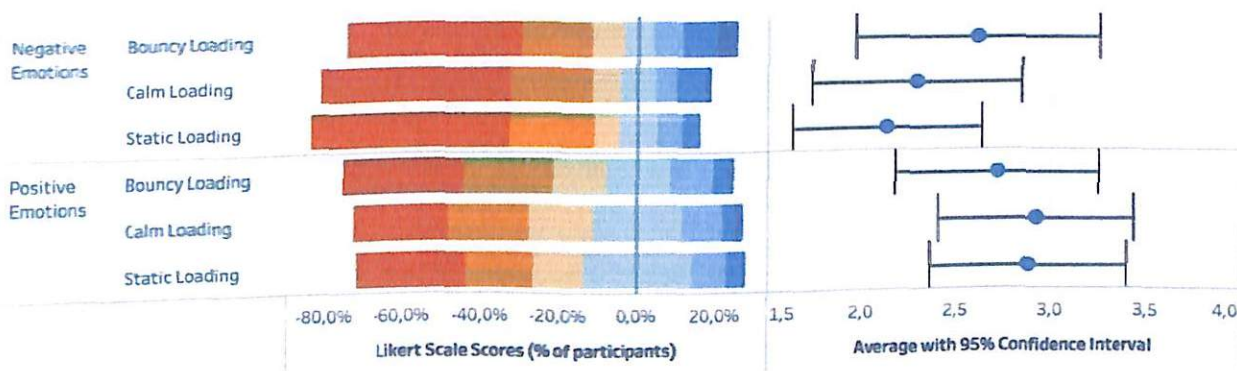


Figure 4.9: The emotion components of meCUE have descriptive statistics.

Transition animations

On the meCUE questionnaire, there are two sets of Likert scales: one for happy sentiments and the other for negative feelings (see Figure 4.10 for details).

Negative

The Greenhouse-Geisser estimation of sphericity deviation was 0.952. The kind of transition animation had no effect on the construct negative feelings of the UX, according to the meCUE data, $F(1.382, 64.751) = .378, p = .678$.

Positive

The Huynh-Feldt value for the sphericity deviation was 0.859. The kind of loading animation had no effect on the construct good emotions of the UX, according to the meCUE data, $F(1.727, 58.378) = 1.394, p = .254$.

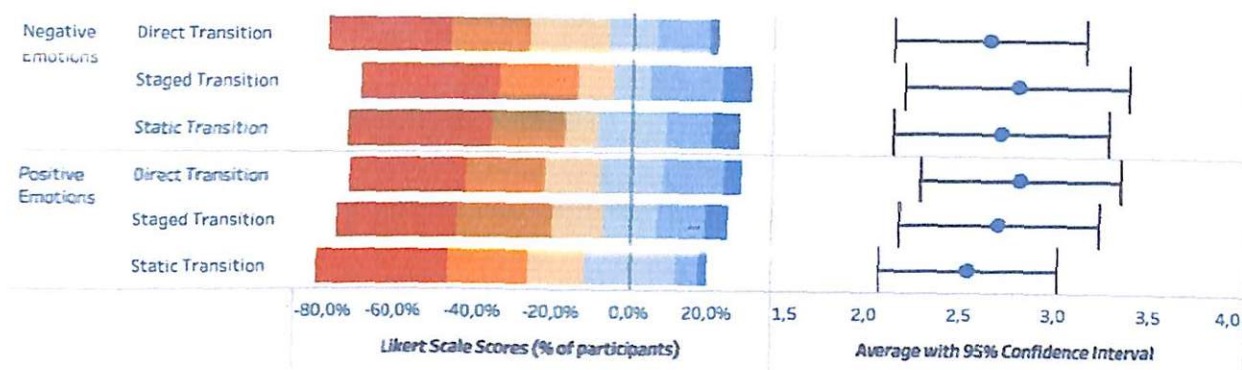


Figure 4.10: The emotion components of meCUE have descriptive statistics.

4.1.3 Overall UX (n = 73)

As measured by the meCUE questionnaire, the entire user experience is shown in Figure 4.11.

Task Name	Mean	SD	N
Bouncy loading animation	2.75	2.79	73
Calm loading animation	3.38	2.08	73
Non-animated	3.38	1.65	73
Direct transition animation	2.62	2.26	73
Non-animated transition	2.62	2.13	73
Staged transition animati..	2.55	2.22	73

Figure 4.11: Measuring the overall UX using the meCUE questionnaire yielded descriptive data.

Loading animations

An estimate of sphericity deviation by Huynh-Feldt was 0.927. According to the results of meCUE, the kind of transition animations had a significant impact on the measure of overall UX: $F(1.854, 133.458) = 4.294, p = .018$. There were significant differences in the bouncy load level's mean and other averages, according to Bonferroni corrections. Even though the dynamic loading condition ($p = .081$) was lower, the tranquil in as ($p = .045$) was still lower. It is shown in Figure 4.12 that the loading animations have an average overall UX rating and accompanying 95 percent confidence ranges.

Transition animations

The Huynh-Feldt value for the sphericity deviation was 0.925. The kind of transition animation had no significant effect on the indicator of total UX, according to the meCUE findings, $F(1.847, 133.154) = .067, p = .935$. (Figure 4.13)



Figure 4.12: The overall UX of loading animations is rated with a 95 percent confidence interval ranging from -5 (bad) to 5 (outstanding) (good).

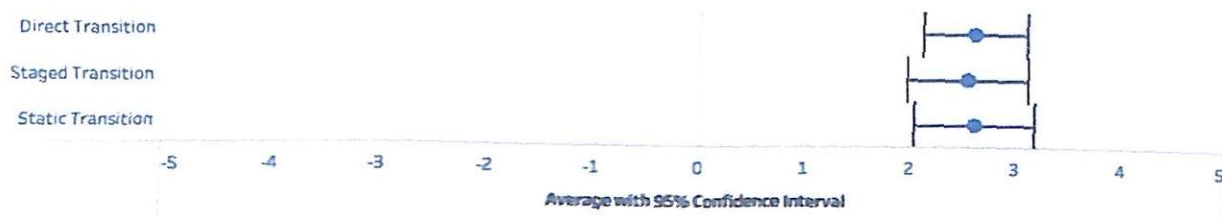


Figure 4.13: The overall UX of loading animations is rated with a 95 percent confidence interval ranging from -5 (bad) to 5 (outstanding) (good).

4.2 Comparison of Results

4.2.1 Questionnaire for comparison (n = 73)

Participants were invited to fill out surveys after an overview and presentation of the animation changes. Both bouncy and silent loading animations had a considerable impact on the visual appeal of the graph and the ease with which it could be comprehended. Results are shown in Fig 4.14.

To compare the mean Likert Scale scores for both animations, a paired t-test was used. In terms of $t(80) = -5.81$, $p = 0.00$, this animation differed significantly from the calm animation ($M = 2.85$, $SD = 1.75$). The Likert evaluations for both animations on the questions were completed in the same way as the graph's animation contributed to the graph's beauty. A significant difference in ratings was found between the bouncing ($M = 3.62$, $SD = 1.78$) and the serene ($M = 5.41$, $SD = 1.52$) animations ($p = 0.00$, $t(80) = -6.34$).

Although the animation was merely a visual depiction of the chart, participants overwhelmingly felt ($M = 4.20$) that perhaps the calm animation helped them better comprehend it.

Animations were more interesting to look at than they were to learn from, but they were still useful for getting information across.

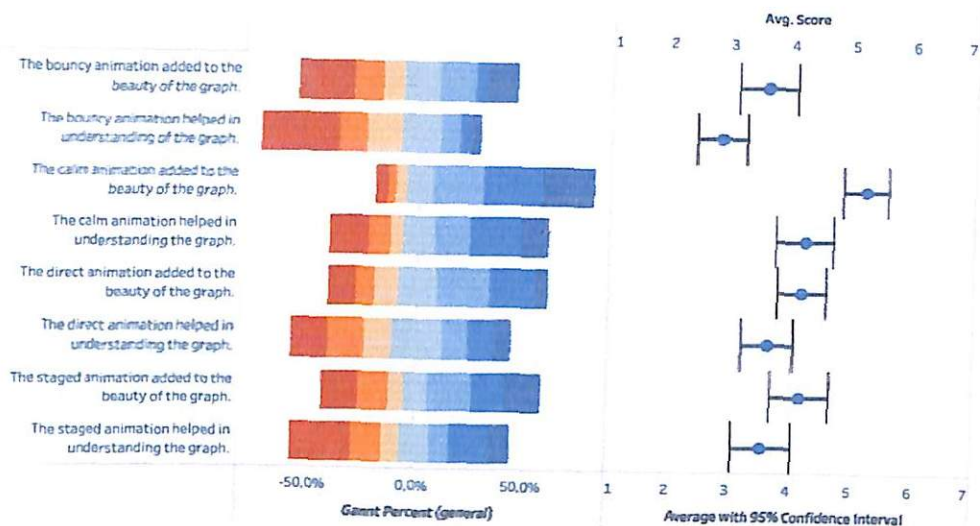


Figure 4.14: For all animations, responses on the Likert - type scales of the comparative questions

4.2.2 Graphs that are preferred (n = 73)

In all rounds of the experiment, participants were asked to choose the graph condition they liked. More people (n = 47) prefer smooth animations over bouncy animations and non-animated animations while loading a graph, respectively. There was no measurable difference between those who liked animation graphs (n = 27 and 28) and those who chose non-animated graphs (n = 23). Figure 4.15 illustrates these findings visually.

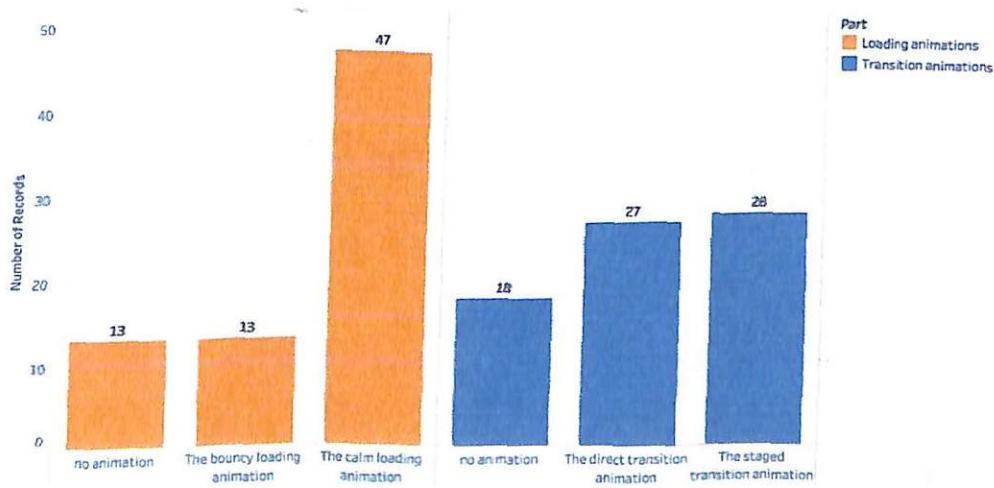


Figure 4.15: Optimal circumstances with the loading animated conditions on the right and the transition animated conditions on the left

Figure 4.16 shows that people who prefer animated scenarios have a lower average age as those who favour non-animated ones. In spite of the outlier, the mean and 95 percent confidence interval show that animated circumstances are

favored by much more young people, whilst non-animated settings are chosen by even more senior people. This seems to be influenced by an outlier (Figure 4.17).

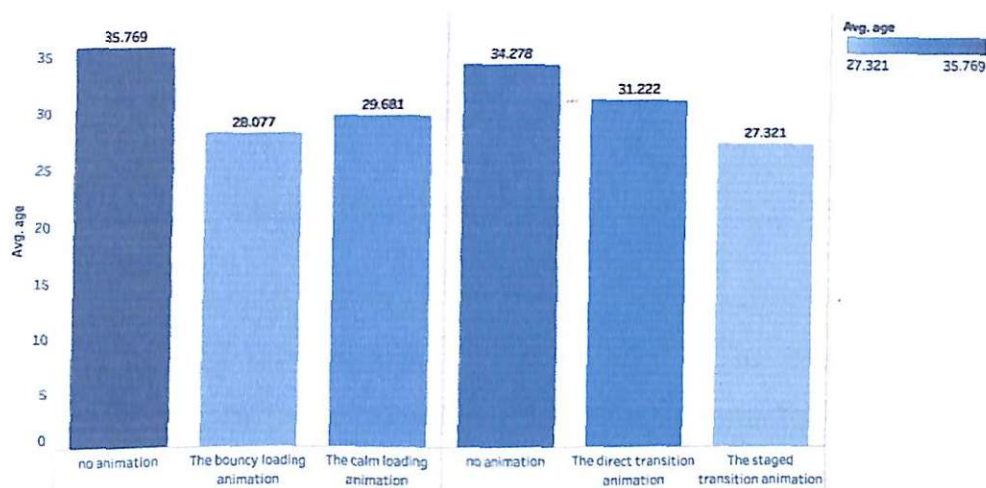


Figure 4.16: The age range of the people who favor a certain condition

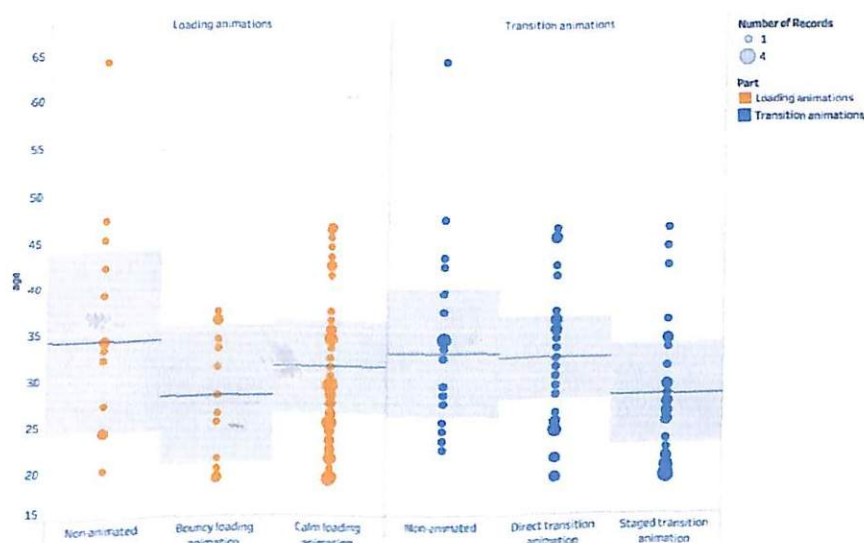


Figure 4.17: Age of the participant groups that favor a given situation (median and 95 percent CI).

4.3 Optional qualitative findings (from n = 73)

Figure 4.18 lists the number of qualitative responses. The animated circumstances elicited somewhat greater (optional) emotions in both segments.

The qualitative responses to the loading animation circumstances were mapped from -2 (negative) to 2 (positive). Figure 4.19 depicts the results of this mapping. When it comes to loading animations, it's clear that the bouncing animation

Task Name	
Bouncy loading animation	19
calm loading animation	19
no loading animation	12
Direct animated transition	11
Staged animated transition	16
non-animated transition	9

Figure 4.18: The number of qualitative responses based on the circumstances receives more negative feedback than the quiet and non-animated situations. The peaceful animation has received the most favorable feedback. Both animated circumstances have more critical and positive comments linked with them when it comes to transition animations. They generate more negative and positive responses.

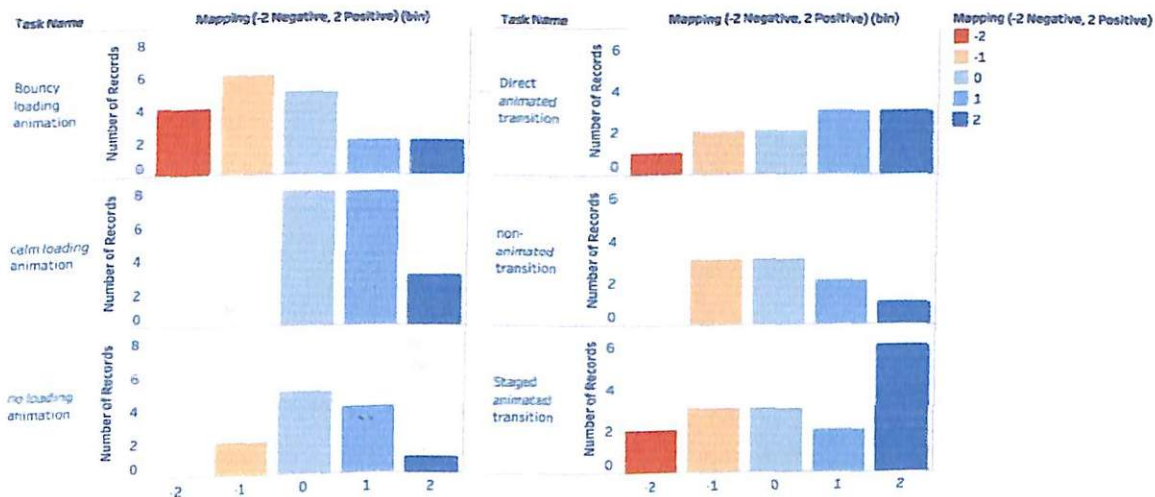


Figure 4.19: A summary of the qualitative mappings between -2 (negative) and 2 (positive) (positive)

4.4 Additional evaluations

4.4.1 The mean amount of clicks for condition (n = 73).

Respondents were tallied on the amount of times they changed their opinions in all conditions. The click - through rate did not seem to be affected by the circumstances in either section of the trial. Figure 4.20 shows the findings.

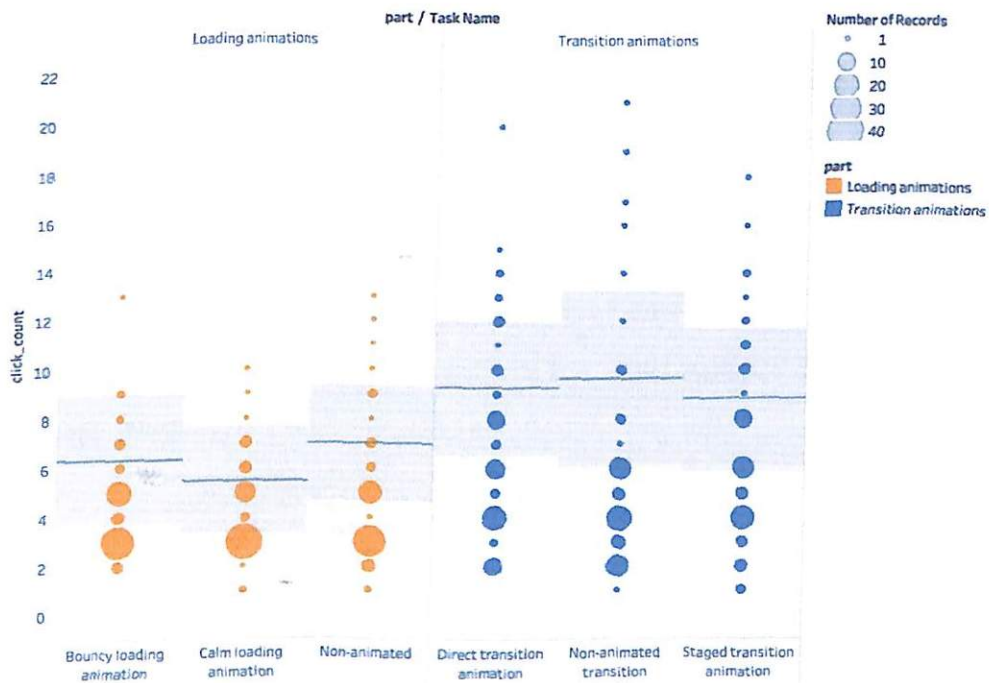


Figure 4.20: The 95 percent confidence intervals for the overall number of impressions (switches in between two views) each condition for the loaded animations and transition animations.

5. Discussion

For both loading and transition animations, participants' emotions were quite diverse. Even when it comes to the transition animations, there is a wide range of preferences among participants. Some people find staged animation to be an advantage, while others find it unpleasant and unnecessary. Having made this difference, it's clear that app developers must know exactly who they're building their apps for. Animations are preferred by younger individuals whereas non-animated states are preferred by older people. The meCUE questionnaire indicates that there are only very minor variations between the two scenarios. In contrast, there is indeed a clear attraction for load animations, which the meCUE surveys cannot identify.

5.1 Animations for loading

Respondents seem to favor the calming loading animation. Overall, meCUE's evaluation of user experience suggests that the most relaxing animation has the greatest UX, followed by a condition with no animation, which receives a score that is virtually comparable. The bouncy animation condition has a worse overall user experience than the other options. The click-through rate demonstrates that users move between two views on average six times under all settings, indicating the same degree of engagement. A non-animated state has the same overall user experience as a calm animation state, which is surprising considering the prominence of serene animations in the gaming industry

The usefulness, functionality, and aesthetics of a product are all affected by the loading animation settings (negative and positive). Even though the bounce animation seems to trigger more negative than good feelings, the findings are nonetheless noteworthy. As a result, this data cannot explain the wide range in

liking and overall UX. Although the questions don't seem to be sensitive enough to quantify small changes, the product quality constructs don't seem to cover the essential condition differences, which would indicate a problem with content validity. It's also questionable whether or not the number of participants has any bearing on the bad sentiments elicited by the cartoon's bouncing animation. People have a hard time connecting graphs and statements about emotions, as seen by the poor scores on these claims. A sampling of the qualitative comments from participants includes "don't try to tie visuals to sentiments" and "I believe the terms are unusual; I don't have a unique experience with graphs."

Comparison questionnaire findings suggest that silent animation is preferred in terms of user experience and preference. [9] For both "aesthetic quality" and "useful for understanding," the quieter animation is 1.5 points better than the bouncing animation. When the contrast between the two scenarios is clearly stated and made plain, people appear driven to give an opinion. The difference between the "bouncy" and "calm" steering animations may have influenced this, as may the words used to characterize them.

Qualitative feedback indicates that the final product is more in line with participant expectations, which is a good sign. This comment was made prior to the comparative and animated explanation. Respondents often complain that the bouncing loading animation is "distracting" or "irritating." Despite the meCUE survey's failure to identify an emotional reaction, this indicates why respondents prefer silent animation over active animation. $n = 10$ negative comments are associated with the bouncing animation, whereas $n = 0$ negative comments are associated with the calm animations. Non-animated graphs are described as "simple but effective" and "not exciting yet convey the data well" by participants. Participants The non-animated control (liked by $n = 16$) and the tranquil animation condition (favored by $n = 51$) had almost comparable numeric UX, but qualitative feedback indicated a considerable difference in preference. Despite the fact that both animated and non-animated replies are often good, a tranquil motion receives twice as many positive comments ($n = 19$ affirmative) like a non-animated variant ($n = 10$).

Accordingly, although the measured UX with the non-animated graphic is almost comparable, users clearly prefer the calming animation. The meCUE survey cannot measure the negative effect of the bouncing animation on the user experi-

ence. It's possible that the popularity of the peaceful animation condition in the produces quality is due to participants' dislike of the non-animated graph. However, the quantitative survey findings do not reflect this. Thus, the results show that the meCUE survey did not sufficiently capture all of the user's experiences and feelings.

5.2 Animations for transitions

Crossover animations have a minor preference over those without whenever it comes to changeovers. The meCUE poll indicates that the animation conditions have a slight advantage in terms of overall user experience. This suggests that participants change between both the two images on average nine times in all scenarios, which is consistent with the click-through rate (the rate at which participants move between the two views).

Loading animation parameters have a consistent effect on product qualities and emotions (negative and positive). Animated transitions get a little aesthetic advantage over non-animated transitions according to the meCUE questionnaire, but the difference is not statistically significant. Despite the fact that the variance is not meaningful, the meCUE data show that the variation in choice is mostly due to aesthetic differences. The transition animation might theoretically improve usability by helping participants comprehend the relations between the main views of the chart; however, this is not evident in the meCUE data.

When comparing the qualitative input to the preferences, fairly comparable scores are discovered. Positive and negative reactions are more qualitative in both animated and non-animated settings. It can be observed, for example, that some individuals find the produced animation irritating and superfluous, while others praise it. The animated circumstances are the source of both extremely favorable and very negative comments.[6]

In terms of 'added aesthetics' and 'helping in the comprehension,' the two animation score pretty similarly on the comparative questionnaire. It's worth noting, though, that the staged animation lasted almost twice as much time as the direct rendering. When opposed to the load animations circumstances, the higher standard deviation shows how split views are, resulting in a less obvious average choice.

In conclusion, when it comes to transition animations, individuals have diverse tastes. According the meCUE data, both animation transitions have a modest average preference, which is attributable to the greater visual quality. However, neither of the meCUE values were significant. When looking at individual individuals, there are those who have a strong preference, which is balanced out by others who have had opposing experiences. Since no two users are the same, there is no such thing as a "one size fits all" approach to user experience.

5.3 Implications for measuring user experience

Overall, the meCUE questionnaire findings reveal relatively comparable responses for the circumstances, which is most likely due to the little variances between them. Except for the 'overall UX,' the meCUE questionnaire findings reveal some variances in product attributes and emotions, but none are significant. It's hardly surprising, therefore, that these findings don't always explain for variations in desire. A comparison of the situations may be necessary to determine why some individuals like a given image with accompanying animation over others. According to participants, images and contrast are given more importance and are seen as a preference. This supports this theory. In the current meCUE questionnaire statements, this point of view is simply not possible to be captured.

Increasing the sensitivity of this survey by include additional dimensions in the CUE model's features of the product is one possibility. Due to the component nature of the review procedure, certain buildings may be included and others may be excluded. Identities or statuses would not be included in this research since they have no impact on information visualization. As a result of the difficulties participants had in relating specific emotions to graphs, questions on emotions will need to be re-examined in future studies. An animation's impact extends beyond aesthetics to include characteristics like interpretation and engagement that aren't adequately captured by the existing set of meCUE questionnaire questions, as previously mentioned. There must be an effort to define all product characteristics for a domain, bearing in mind that all these attributes might change depending on the application. "

As well as blurring the distinction between product attributes and sentiments, it may be beneficial to do so. According to Aranyi and van Schaik, under the

CUE model, interaction characteristics and emotions may be directly linked to one other. It is possible to offer these features as product aspects of UX in this way, even if they are intertwined with emotions. User experience (UX) may be improved if a clear delineation between product quality and customer emotion is established.

In addition, the circumstances with greater aesthetics also scored better on usability, despite the fact that loaded animation improves nothing but aesthetics. This result is consistent with Tractinsky's aesthetic-usability effect, which states that if something is more attractive, it is also viewed as more useable. This demonstrates that perceived and objective usability vary, but it also raises the issue of how adept people are at identifying their UX based on distinct product features. Do consumers always understand why they prefer or even have a richer outcome with a certain system? According to some study, while building a UX, one should watch rather than listen to the user. This is a crucial point to examine in future research using the meCUE questionnaire since the meCUE technique of assessing UX relies exclusively on the user's self-report. This same feature shows that objective behavioral or physiologic data might be a viable option for assessing UX.

Aside from the constraints listed above, another drawback is that user experience might alter with time, and thus a strong first impression does not ensure continued usage. The evolution of user experience over time is seldom studied, and although animations may be entertaining at first, after a few viewings, they may become annoying. Future studies should confirm if this is the case when ever a visualization is used more often. Hedonics are crucial at initially, but characteristics such as usability will become increasingly significant with time. For the animations presented in this experiment, this should also be explored and studied. Allowing users to switch down the brightness animation might result in a more pleasant UX over time.[10]

It was proposed that bigger variations between conditions be explored using the meCUE approach to determine whether larger differences could be evaluated more correctly after it was proved that it was ineffective for analyzing tiny differences between conditions. Qualitative feedback ratings may be suspect since they were only assessed by one person, but they suggest that qualitative strategies for evaluating UX may triumph over quantitative ways when the changes between

situations are minimal. There is a need for further research that focuses on certain user groups since this study has shown that age determines which representations individuals prefer. It's intriguing to see how various user characteristics alter the user experience.

6. Conclusion

"Could the UX of a data visualisation be quantified quantitatively?" was the initial study topic. Exhaustive research in the field of data visualization has yielded a wide range of definitions and conceptions of user experience. The phrase "user experience" still has many varied meanings, as seen in this literature review. Different UX models concentrate on different aspects of the user experience. There are several approaches for evaluating user experience, both objective and subjective. Because the purpose of this experiment was to investigate the user experience of a data visualisation while also achieving a goal, a methodology was built in which instrumental characteristics like usability were well represented. Because information visualizations are dependent on images, aesthetics is equally vital. Because information representations aren't tangible things, factors like identity and status aren't as vital. Based on these criteria, the CUE model seems to be the greatest fit for the data visualization area. In the experiments, this model was employed.

"What parts of the CUE model and also its measuring instrument meCUE may be employed for the area of information visualization?" was the second research topic. There are no major variations between the conditions in the meCUE data, however there are some minor variances. These minor discrepancies are created not just by the delicate nature of the changes between the situations, but also by the diversity of perspectives among the participants. Contrary viewpoints may be cancelled out by averaging findings across this group. The only significant change determined by the meCUE survey was the bouncy animation's 'overall UX,' which was poorer than other two circumstances. Despite the fact that the measured UX is almost identical to the semi-condition, the preferences show a clear preference for the tranquil animation.

First, the product criteria of usability, usefulness, and beauty plainly do not

include all elements of information visualization UX. Each application has its own set of structures for measuring product quality. Future study should establish what additional components need be included to the meCUE questionnaires to apply this to data visualization. As previously said, identity and status are instances of terms that pertain to physical items rather than data visualization. Engagement, interaction aesthetics, believability, and attractiveness, according to other models and theories, might be good candidates for further categories. Future study should determine if these components overlap more with additional variables or together, as well as appropriate measurement questions.

Separating emotion from product attributes is also logically correct, but it is unworkable in practice since people cannot always link emotions to the product features that cause them. In this research, people reported experiencing negative emotions connected to bouncy animation, but this was not included in the esthetic framework. In reality, the CUE paradigm may not be able to separate emotions and qualities as much as it now does since people understand emotional sensations better than they do the product elements that create them. Incorporating user emotions such as "joy of use" and "desirability" into UX design may help users better connect with the product they're using.

Finally, quantitative UX research employing the meCUE approach has several limitations in the context of this study as compared to qualitative research. To begin with, the impact size is quite tiny, implying very substantial changes need a large number of individuals. Second, qualitative research enables participants to openly express their thoughts, allowing for more precise responses as to why a certain depiction is chosen.

When it comes to information visualizations, loading and transition animations play an important role in the user experience. Data visualization may be both improved and harmed by animations depending on the context in which they are used. The calm loading animation was favoured by participants over other loading animations. As an example of a distracting or unnecessary animation, the "bouncing loading" motion was used to detract from the data visualization's overall user experience (UX). If the CUE model is correct, the use of a calm loading animation enhances the user experience in this case. Despite the fact that the meCUE-evaluated UX was substantially identical in the non-animated scenario, this implies that not all parts of the UX were thoroughly studied. There was a

slight preference for both transition animations, but generally, people had a wide range of opinions on the subject. While some participants found the energetic transitions amusing, others considered them obtrusive and intrusive on the ears.

The uniqueness of UX is highlighted by these various experiences. The animation transitions enhanced the UX for one participant, but they were a distracting from the graph's message for others. As a result, just one UX design is not recommended. Deviations among the participants may be reduced by more precisely defining a user group. Furthermore, even if the motion was just for aesthetic purposes, several participants reported improved use of functionality. This program calls into question the validity of inner UX and might be used to argue for more objective UX metrics.

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