Memorability of Data Physicalisation with Relatable Shapes

A thesis submitted to Middlesex University in partial fulfilment of the requirements for the degree of Masters by Research (ST)

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Abstract

This paper describes a user study intended to gain insight into whether users' ability to recall is affected by whether the data physicalisations resemble the actual objects. This study looked specifically at the question, “Will data physicalisations with literal shapes help users to better remember the data , than using data physicalisations with more abstract shapes?”. Over 30 participants were asked to interact with data physicalisations that represents the amount of caffeine in different drinks. The physicalisation either resembles the shape of the actual drink or is a cube shape. The participants were asked to remember the relative order of different drinks in terms of their caffeine amount and their recommended daily caffeine limit. This was tested immediately after the interaction and again one week later. There is no significant difference between the two groups, but there are some interesting observations worth further investigation. Not enough evidence was found to suggest that creating a physicalisation that actively resembles the data topic, makes a difference in the recall ability of the user. The suggestion is that if the data and task are relatively simple (as in this study), the shape of the physicalisation does not further add to the recall ability.

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Contents

Introduction

Figure 1 - Top: Unpainted Wooden blocks and beverage vessels sorted from high caffeine content (left) to low caffeine content (right)
Bottom: Painted wooden blocks and beverage vessels sorted from high caffeine content (left) to low caffeine content (right)

In almost every field, visual metaphors have been used to help communicate and analyse ideas, information, theories and concepts, these have taken various forms, from 2D drawings, to virtual 3D interactive graphs to physical representations. More recently there has been an uptake on using physical representations [1]–[3], known as Data Physicalisations, particularly for making data and various information more accessible and understandable to the general public.

Data Visualisation can be found in books, newspapers, magazines, academic papers and powerpoint presentations. They are often encountered as different types of graphs, charts and pictograms. Data Physicalisations can be found in museums and galleries where artists and scientists have put together physical objects and systems that display information. They can also be found in very rudimentary forms, such as in schools and with children, often as blocks or toys, teaching them how to count.

Both Data Visualizations and Data physicalisations (also known as Physical Data Visualizations) have been known to help users to see the patterns and similarities that are within the data being visualized, helping to process and analyze the data. Research suggests that images are often better remembered than text, and objects are often better remembered than images [4]. Several studies have shown that physicalisations could have a positive impact on recall ability if the participant is interested in and understands the data [2], [5]. The reason may be that spatial layouts are easier to remember with a physical object [5]. According to [6], short-term memory is influenced by haptic interaction, while the use of physical objects takes advantage of active learning and represents data in a salient way [7]. It has also been used to create a greater understanding of the information, whether it is owing to the idea that the visualization gives context to the data, or it just creates a more memorable experience of the data. It also allows for analysis of the data from different perspectives and makes it easier to mentally process complex data and multifaceted relationships [1], [8]–[10].

Despite the recent interest in data physicalisations, there is still a lot of academic research that needs to be done into the processes, strategies and theories.

The purpose of this study is to gain an insight into whether users' recall ability is affected by the shape of data physicalisations, whether it resembles the actual objects or has no similarity in shape. We conducted an experiment where the participants used the physicalisation to learn about the amount of caffeine in common beverages and their Recommended Daily Caffeine Limit (RDCL). RDCL is the maximum recommended amount of caffeine that an individual should consume in a day and is calculated using the weight of the consumer. The participants were split into two groups, the Cube group and the Real group where they received either wooden blocks or beverage vessels representing each drink type. To test the memorability, the participants were given a questionnaire immediately after the interaction, and then given the same questionnaire one week later. Our study did not find enough evidence to suggest that creating a physicalisation that actively resembles the data topic, makes a difference in the recall ability of the user.

Related Works

What is Data Visualisation?

Data Visualisation has been known to help users to see the patterns and similarities that are within the data being visualised, helping to process and analyse the data. It has also been used to create a greater understanding of the information, whether it is owing to the idea that the visualisation gives context to the data, or it just creates a more memorable experience of the data. It also allows for analysis of the data from different perspectives and makes it easier to mentally process complex data and multifaceted relationships [1].

“Visual analytics is the science of analytical reasoning facilitated by interactive visual interfaces. People use visual analytics tools and techniques to gain information and derive insight from massive, dynamic, ambiguous, and often conflicting data.” Within Visual Analytics there are several sub-sections; “Analytical reasoning techniques that enable users to obtain deep insights that directly support assessment, planning, and decision making. Visual representations and interaction techniques that take advantage of the human eye’s broad bandwidth pathway into the mind to allow users to see, explore, and understand large amounts of information at once. Data representations and transformations that convert all types of conflicting and dynamic data in ways that support visualization and analysis. Techniques to support production, presentation, and dissemination of the results of an analysis to communicate information in the appropriate context to a variety of audiences.” This definition was taken from the book “The Research and Development Agenda for Visual Analytics” written by James J. Thomas and Kristin A. Cook [8].

What is Data Physicalisation?

Other ways to help those receiving or analysing information include non-visual sensory modalities; these processes may play to the human sense of smell, hearing, touch or even taste. Here the properties and relationships of the data are translated into different forms, causing both layman and expert to not just understand but also experience the data, which will be more memorable and possibly more meaningful [10]. Data Physicalisations (also known as Physical Data Visualisations) are “artefacts whose geometry or material properties encode data” designed to better support “cognition, communication, learning, problem solving, and decision making” [9].

One of the benefits of Data Visualisation is that it can give the data context or background such that the data is more palatable and relatable. For example, the 2001 installation by Luke Jerram (Figure 2) visualises the effect of the moon’s gravity upon sea levels in Bristol. The installation had a gravitometer which measures the changes in gravity every minute while the moon and earth change their position. These changes control the water levels in three large rotating glass spheres, representing the sun, moon and earth. A friction device further attached to each glass sphere causes the glass to “sing”, this exhibition is used to visualise the rise and fall of tide levels, thus, creating a medium that allows the viewers to experience data which otherwise they may not be able to physically experience as humans are not able to detect such changes in gravity. Many other artists and government schemes have begun to explore these forms of modalities in order to engage diverse audiences to data and make data more accessible. This gives the users an opportunity to process data they would have otherwise not experienced or perceive data differently, allowing for a perspective change and possibly behaviour changes [10]. This is a valuable tool to influence, teach and make the public aware of general problems such as pollution, recycling or healthy living. If the public can experience the data themselves, then the data could be more impactful and be more likely to leave a permanent imprint in the minds of the people, making it more memorable. It is possible that this can be used to implement changes in the thinking and even the behaviour of the public based on the greater understanding gained [10].

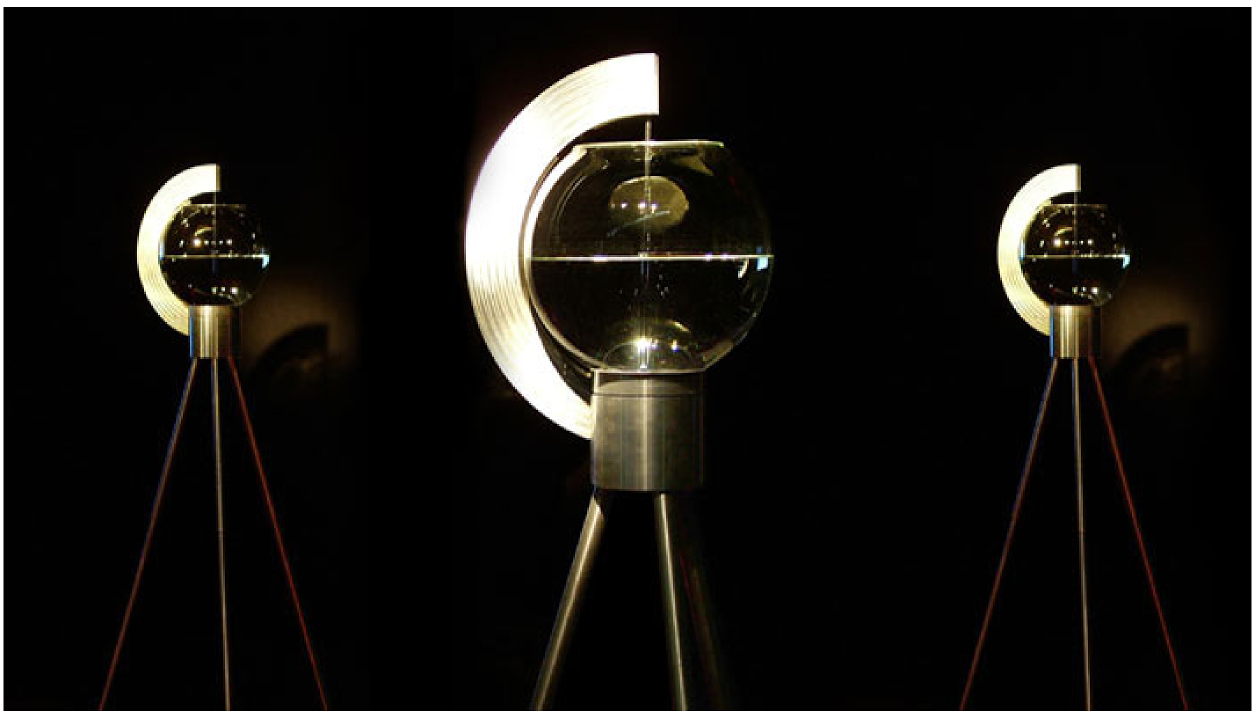

Figure 2 - Tide Installation by Luke Jerram, spinning glass spheres that resonate and “sing” a different note according to the rise and fall of the tide
Source: [11]

Another benefit is that when transforming data into sensual experiences such as physicalisations, not only are the end users such as the public positively affected, those involved in this process from collecting the raw data, to interpreting it are also able to gain from involvement in the process. Experts in the various fields can expand their knowledge and understanding of both their own field and other fields. For example, in an installation site, where solar wind data is transformed into sound, the physicists can learn about music, and the musicians get to learn about physics and astronomy. However, it also encourages the physicists to see the data from a new standpoint, and even encourage the musicians to perhaps approach music in a different way which can be beneficial for both parties. Collaborations such as these also encourage the public to see the two fields differently, possibly making one field more approachable, and the other more “serious” [10].

Such interdisciplinary collaborations cause both the scientists involved and the artists to become more aware and knowledgeable in the various fields, but also gives all involved a “fresh” view on the data leading to different discoveries and possibly a deeper connection to the data more than before [10].

Personalising data visualisations & physicalisations

[12] and [13] argue that individuals enjoy using physical artifacts to express and represent themselves, such as medals & trophies displayed in public view of homes, or photographs and drawings on fridge doors. These displays are called autotopography which can serve as a memory landscape for the owner.

Similarly, S. Houben et al noted on the benefits of personalising physicalisations. They conducted experiments investigating if Physical Ambient visualisations in the home will encourage users to interact, further investigate and understand the data collected from their immediate environment, to hopefully bridge the gap between non-expert users and their data. The designers of Physikit wanted to use Physikit as a way to cause the data to be more relatable to the user, by collecting data about the user and allowing them to map the data to different Physkit data representation boxes [14].

They undertook an experiment that takes CO2 levels, NO2 levels, light levels, humidity, noise levels and temperature readings from participants homes, and then gave them four interactive cubes that represent the collected data through movement, vibration, air and light and allowed them to map the data to the cube Physicalisations as represented in Figure 3. The experiment was split into two parts, in the first section, the participants were given the Smart Citizen Kit (SCK) which is an open hardware sensor kit that collects the data, creates visualisations for the data and uploads them to a public website that allows all users to see their data and others data. During this first part of the experiment, the participants reported that they found it difficult to understand the data and the visualisations, and that the kit became invisible after a while, so the participants lost interest in the data and the kit [14].

The second part of the experiment involved giving the participants the cubes and allowing them to map the data collected to the visualisations. Here the creators used the task of mapping to engage the user more into the data and into the physicalisation itself. Since the users were allowed to decide what physicalisation corresponds to which data set and were able to personalise the different actions of the physicalisations, they were able to read and understand the data more. They also learned how the physicalisations worked for themselves, and some even used this information to make changes to their household based on the data they received. They found that by being in control of the data distributions, deeper interest in the data was cultivated as the users then started to look at the raw data more and after a short time spent watching and manipulating the physicalisations, they were able to understand the raw data better. Some users even began to explore more into the data field, comparing the data that had been gathered from their home, to data from other homes and other sources. Users also found that they altered their surroundings in order to change the results from the pysicalisations, showing a direct correlation between their interaction with the physicalisation and increased impact that the data and physicalisation had on them [14]. Here we can see a direct correlation between the physical interaction with the 'physicubes' and the engagement and understanding of the users.

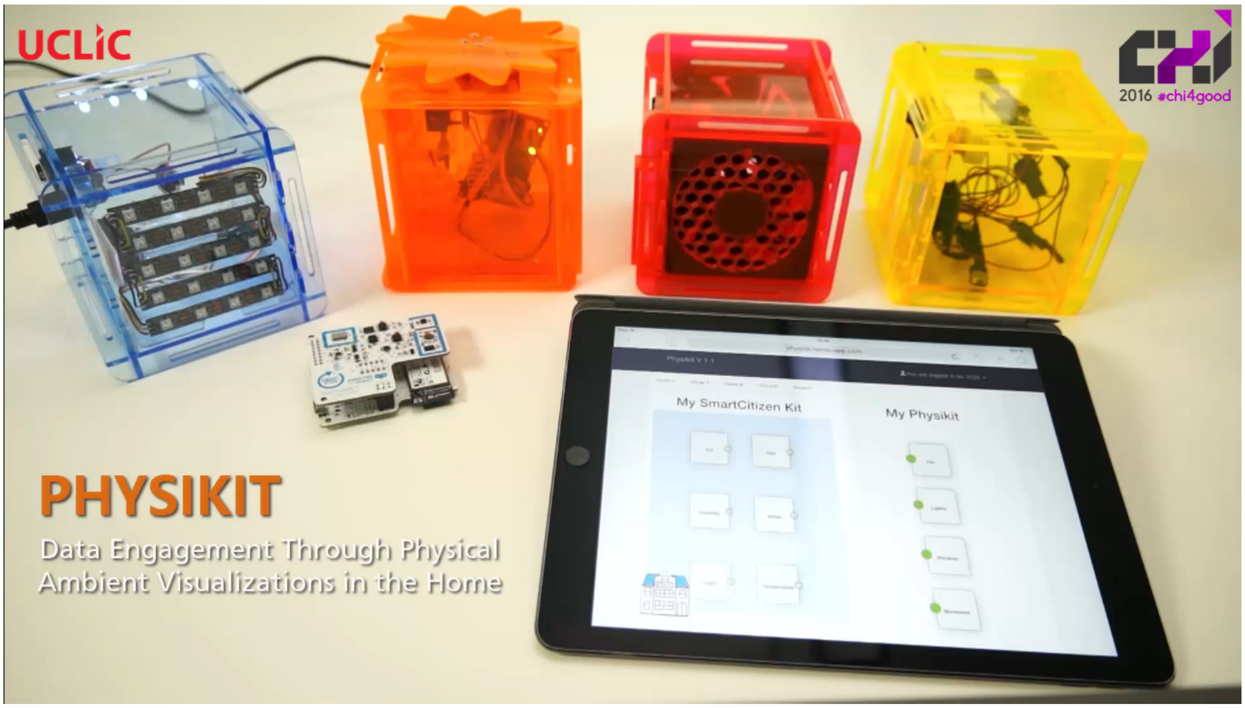

Figure 3 - PhysiKit Data Cubes
Source: [15]

Research has shown that physical and tangible interfaces can increase the awareness and participation of users through their physical properties [1], [10], [14]. Suggestions have been made that physicalisations that are personalised to or by the user are more meaningful to the user [14], [16]. Khot et al. designed a system called SweatAtoms that builds data sculptures that represent the heartbeat data of a user during physical activity. They suggest that if an activity does not provide users with the options for creativity and self-expression, users often alter their physical activity to make themselves feel autonomous & creative. This can sometimes manifest itself in users intentionally running in patterns that resemble genitalia (which would be visible when checking the route of their past runs in their exercise apps) [16].

They argue that because their data sculptures are produced by the user's unique data (as every session of physical activity will cause different heartbeat data results), each data sculpture will be unique in its design. Therefore, users may find these data sculptures more meaningful as each one will be different for each user and each activity session. It may even inspire the user to do exercise differently to try out new patterns to form different data statues [16].

Memorability

Studies have shown that memorability is often inherently intrinsic: what makes visualizations memorable for some people will probably work for many others [17]. The study suggests that diagrams and pictorials are among the best remembered visualizations, followed by more unique visualization types such as trees and networks. Properties, such as color, shape, and size, can help to make visualizations more memorable [17], [18]. Other factors, such as human recognizable shapes and objects (humans, cars, animals, trees, etc.), may also have similar effects.

The role of Images & Visual Aids

In 1983, Edward Tufte coined the term “chart junk”, which is also more kindly known as “embellishments”, which he defined as “ink that does not tell the viewer anything new”. He also defined a term “data-ink” and “the non-erasable core of a graphic”. These terms have been the basis of the debate as to how to appropriately embellish or not embellish data graphics. Essentially, Tufte and others were of the mindset that data graphics should only consist of the bare minimum needed to relay the data to avoid distraction, aid interpretation effort and increase comprehension of charts [19]. However, various chartjunk and embellishments are still actively used throughout data visualisation by data visualisation designers [20]–[23], which in recent years has led to a debate about which viewpoint is correct.

Investigations have found evidence that suggest that when the user has unlimited time to process the information, various levels of chart junk can increase long term memorability of the data and that accuracy in reading the charts is the same as with charts free from embellishments. However, this study used charts with only up to only a small number of data points (around 5 data points) [21]. Another study found evidence to suggest that embellishments could also increase short-term memorability of the data and that they can lead to a shorter time needed to process the data. However, this study too used charts with a relatively small number of data points (around 10 data points) [20]. [20], [21], [23] studies found that most participants preferred the embellished charts as they were more interesting, more attractive and some claimed that they were easier to remember. Some work has also found that embellishing data with colours that are related to the data can increase the speed of finding information in a visualisation [18]. Brady et al. found that category labels that actively connect shapes with the users previous stored knowledge are easier to remember. They also found that when users are presented with a whole bunch of items to memorise that are of the same item type, they are easier to remember when as individuals they are quite distinctive (such as different types of knives), compared to if they are conceptually similar (such as different types of salt and pepper shakers) [24].

Haroz et al. compared various pictographic graphs (with pictographic representations of the real object referred to in the data) and simple barcharts. They suggest that pictures provide multiple cues for encoding and retrieval of memories, which can help to provide the user with a rich set of things that allow the user to create deeper encodings of the data, thus helping them to remember it better. They compare the notion that returning to a physical space where information was learned, can indeed help a person to remember the things learned in that physical space, with the imagery of pictographs potentially helping the user to recall the image of the pictograph and thus help them to remember the data associated [18].

Unitisation

S. Houben et.al. suggest that sometimes the public are unable to interpret or use the data that is available to them due to the lack of proper context and framing for the data, making it inaccessible even if it is physically accessible. They argued that providing physical, tangible and reconfigurable “physicalisations" that match the needs and interests of the user will encourage them to discover and understand the meaning of the data that they collect and decide for themselves how to best use and share that data [14].

Concrete scale is the “process of visually relating complex measures with familiar objects from the real world”. This makes measures that use complex, unrelatable, un-experienceable or generally conceptually-hard-to-grasp magnitudes and units easier to understand and remember. This process can include analogies, unitization, anchoring and adjustment. This allows the observer to “break down the scale through smaller comparisons” which usually helps the observer to have a simpler and easier mental model of scale. Unitization is “redefining an object as a new unit of measurement for assessing the magnitude of other objects in terms of this new unit. It results in relations of the form ‘A accounts for n instances of B’, where B is the new unit.” [25].

Concrete scales rely on simple and familiar concepts and relations that allow the observer to easily make comparisons, and are often used in education and decision making settings. They can be used when trying to grasp measures of things such as the scale of nano-particples, or the distance between the earth and another planet. These are used to help form estimates that are as accurate as possible. This links in with [24] that claim that the reason why people are better at remembering scenes and real-world objects rather than lots of random colours, is because the user has a built-in visual knowledge base for encoding those things, and has previous stored knowledge on the item or scene.

The concept of unitisation is specifically breaking down a unit and using a more known unit to re-express it, whether bigger or smaller. It is applied in the study during the process of creating the physicalisation in this study, where the unit of caffeine in a participant's RDCL is not just shown in terms of *mg* of caffeine, but can be represented by a number of certain drinks. Here, A is the amount of caffeine in the Recommended Daily Caffeine Limit in *mg*, B is the number of drinks that is equivalent to, so B becomes the new unit to represent the RDCL.

Physiclisations Vs Visualisations

Khot et al. note that incentives are important to sustain users interest in an activity, and acknowledge that there are benefits to virtual reward to support activity & interaction. However, they suggest that virtual rewards are not always chriisted and may not be as memorable as a physical reward that can be displayed in the real world. They also touched on the fact that physical souvenirs are still bought and received as they can be more cherishable and meaningful than virtual objects because of their visibility and low replication possibility [16]. Research has also shown that physical and tangible interfaces can increase the awareness and participation of users through their physical properties [14].

In a study by Simon Stusak, et al. they found that indeed, the data physicalisation led to significantly less information decay when compared to an onscreen visualisation. Here they studied the effects that physicalisations have on implicit memory, but they compared a static data physicalisation (Figure 4) with a static data visualisation on an iPad. They presented the data visualisation on the iPad so that both the visualisation and the physicalisation were similar sizes, which was important because they were specifically investigating the effects of the modality of the visualisation, rather than the specific interactions with it. This was a between subjects experiment with 40 participants. Each participant received either the physicalisation or the visualisation, they were then asked to study it and state aloud all the things they noticed about the information. The experimenter would then ask them specific questions from a list of predefined questions to support the participants knowledge, and make sure each participant had the same level of knowledge. Immediately after exploration time, the participants completed an online quiz, and then completed the same quiz two weeks later. The quiz included three sections of questions, *extreme values* (e.g. “Which country has the most trust in its government?”), *numeric values* (e.g. “In Brazil, only 15% have trust in their government.” Possible answers: “True”, “False” or “I don’t know”). The last section was *facts* (e.g. “Germany has more trust in its government that Brazil.” Possible answers: “True”, “False” or “I don’t know”) [2].

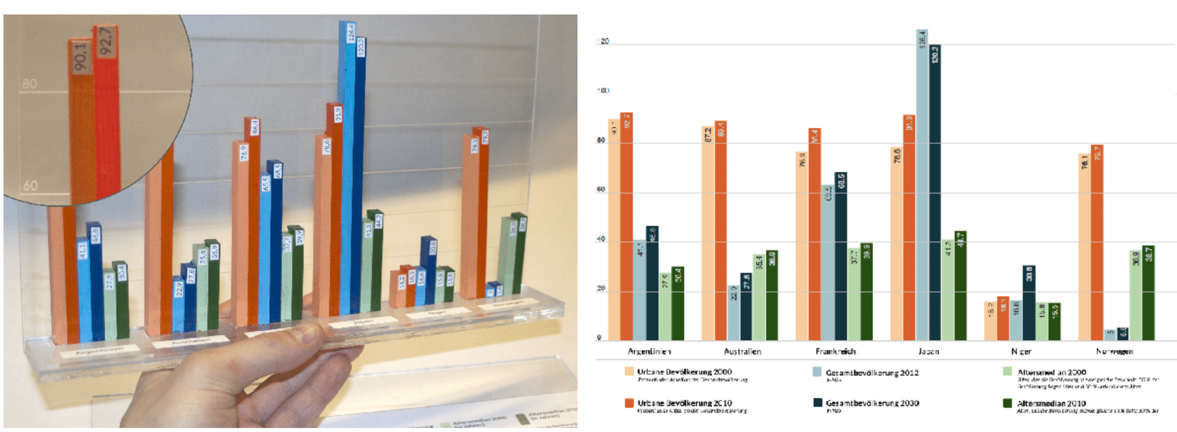

Figure 4 - Static 3D Data Visualisation (left), Image of Static Data Visualisation that would be shown on iPad (right)
Source: [2]

They found that overall and for the *Extreme Values* questions, participants that had the visualisation had better immediate memory recall, however for the delayed recall, the participants that had the physicalisation had better delayed recall. From the *Numeric Values* section, the participants with the physicalisation had better immediate recall and better delayed recall. However, for the *Facts* section of the questions, the participants with the visualisation had better immediate recall and better delayed recall. Stusak, et al. attributed the high recall of the visualisation participants to the process of verbally sharing the facts found during the exploratory session, which may have helped some participants to remember more than the actual visualisation itself [2].

Simon Stusak, et al. conducted another study to better understand what characteristics of physical bar charts have the most impact in terms of memorising information. They compared 2D (paper strips) and 3D (wooden blocks) token based physical visualisations using quizzes immediately after interaction with the physical visualisations and a quiz one week later. They found that with one dataset, the 3D visualisation caused a much better recall than the 2D visualisation. However, they also found that one of the two datasets were said to be too abstract and not interesting, with this dataset, the general recall for this was very low and there was very little difference between the 2D and 3D visualisation results [5].

Participants were asked to assemble a visualisation using the box of paper strips or wooden blocks. Each participant created a visualisation with both paper strips and wooden blocks, as shown in Figure 5, from a given data set, but half of the participants made visualisations with the paper strips first and the other half with the wooden blocks first. The participants then proceeded to answer questions about each data set, such as “name the countries with the highest and lowest values for each category”. They also had to give specific data points, compare specific bars and state the summarised values. The participants were encouraged not to intentionally try to memorise the information and were asked to leave questions that they were not sure about blank rather than guessing. The participants went through another series of questions one week after the initial experiment day. Stusak, et al. compared the number of correct answers from both questionnaires, the study leader observed the sessions, the study sessions were also recorded, semi-structured interviews were had with participants to gain extra insight and demographic information was gathered at the beginning of the sessions [5].

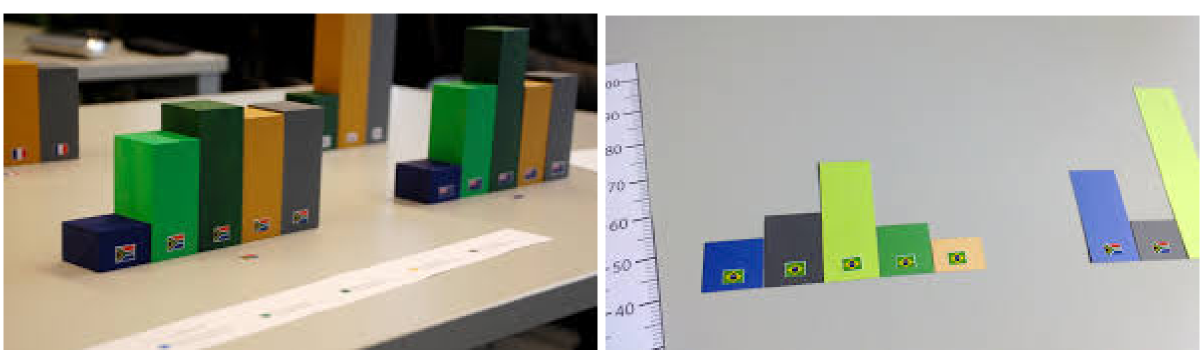

Figure 5 - 3D wooden block physical visualisation on the left, 2D paper physical visualisation on the right
Source: [5]

Data Physicalisations are used to engage people in data exploration adding an extra dimension of interactivity with the data, particularly with shape-changing technology. Technology such as EMERGE (a physically dynamic 2.5D bar-chart) shown in Figure 6, increases the possibility of deeper understanding of and engagement with the data that on-screen visualisations and static physical data visualisations fail to take the user [9], [10]. [5] suggest that yes, spatial and tangible properties of a physical visualisation can enhance the impact of the data, however, the data must be of interest and easily comprehensible to the user or else these properties will have very little impact, echoing the findings of [14], [16].

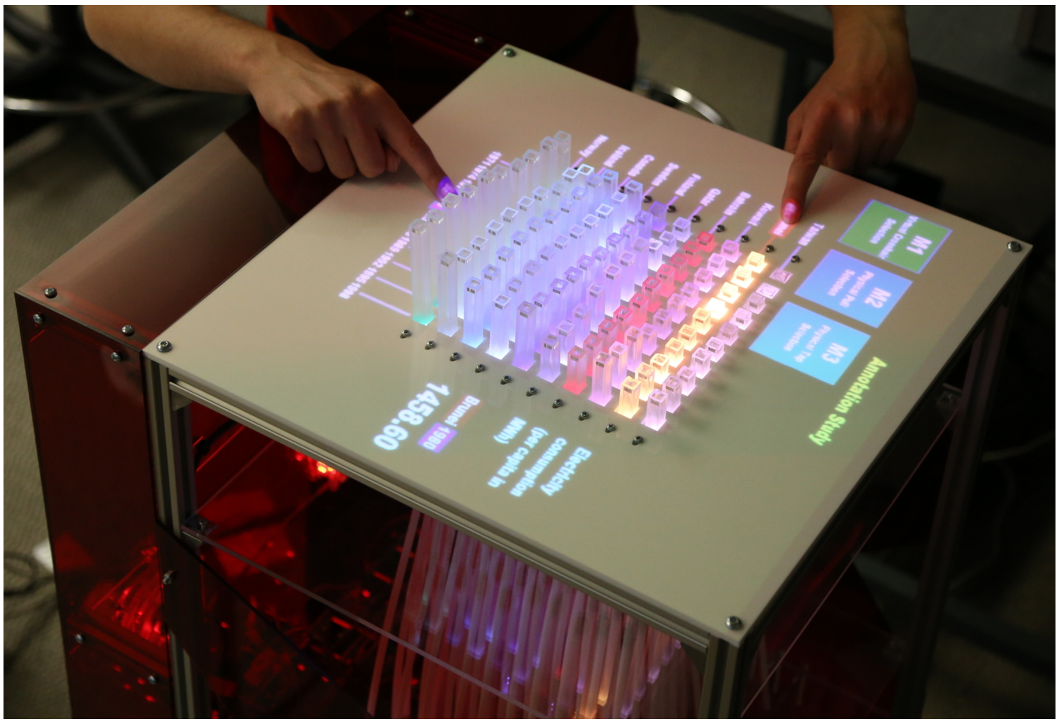

Figure 6 - EMERGE (a physically dynamic 2.5D bar-chart)
Source: [9]

Jansen, et al. did a study comparing on-screen 3D visualisations & 3D physicalisations. They found that their 3D physical bar charts greatly outperformed the on-screen 3D bar charts. Their suggestion is that physical touch is an essential cognitive aid and visual realism may help users [3].

My Study

The key points that will be taken forward into this study is the importance of personalising the data to the user, as well as making sure that the benefits of handling the physicalsation are maximised by creating tasks that will encourage the user to pick up, move and actively analyse the physicalisation. The comparison in this study is taking the work of Brady et al. [24] one step into the world of physicalisations, comparing a standard cube shape to the real-world shape of common caffeinated drinks, that potentially has more previously stored knowledge, and possibly a larger built-in visual knowledge base that directly links to the data.

The actual experiment will follow a similar pattern to Stusack et al. [2], [5] where the participant will interact with the physicalisation, then immediately after do a quiz, and then another quiz, a set time after.

Research Question and Hypothesis

We know that the spatial and tangible properties of a physical visualization can enhance the impact of the data, and thus the memorability of the data [5]. Research has also shown that physical and tangible interfaces can often increase the awareness and participation of users through their physical properties [10], engaging them in data exploration and allowing them to experience the data. Data exploration can allow the user to process the data themselves, adding an extra dimension of interactivity with the data. However, allowing the personalization or reconfiguration of the physicalisation has been shown to potentially allow the user to explore the data in a way that relates to them individually, which also could assist in understanding the underlying data presented and thus possibly helping the memorability of the data. [10], [14], [26]. These findings were used to design this study, encouraging the participants to make the most of the spatial and tangible properties of the Data Physicalisation by picking and moving them, but also giving them the opportunity to personalise the Data Physicalisation to themselves.

This study looks into the question of “What factors of a physicalisation can help users remember data?”. Particularly, we want to gain an insight into whether users’ recall ability is affected by the shape of data physicalisations, i.e., whether it is more literal and relatable to the specific data versus more abstract.

The data used in this study is the amount of caffeine in different types of drinks and the participants Recommended Daily Caffeine Limit. This data was chosen because caffeine is commonly consumed by a lot of the world so it is possible that the participants may have some interest in it. The personalised Recommended Daily Caffeine Limit could be new and useful information for the participants, that could help to inform their future caffeine consumption, It was important that there would be some interest in the data by the participant as Stusack, et al. found in [5].

Therefore, this study looks at the question “Will data physicalisations with literal shapes help users to better remember the data , than using data physicalisations with more abstract shapes?”

More specifically, this study will tackle the question “Will representing the caffeinated beverages literally (e.g. a Costa take-away cup to represent a coffee) help participants better remember the relative order of the amount of caffeine in a beverage and/or their recommended daily caffeine limit instead of representing the caffeinated beverages abstractly (e.g. a block with a label showing which beverage it represents)?”.

The hypothesis is inspired by the previous studies by S, Stusak, et al, [2], [5] that found that users of the physical bar graphs had generally higher recall results than the users of the visualization or the 2D paper visualization. Their studies did not investigate the impact of different shapes possible in data physicalisation.

This study will be specifically evaluating the following hypotheses:

1. *Representing the data via data physicalisations with literal shapes will help the user to better remember the data presented to them.*

Specifically the hypotheses evaluated are:

2. *Representing the beverages with a data physicalisation whose shape resembles the actual drink container will help the participants better remember the* ***relative order of the amount of caffeine in a beverage*** *than representing the caffeine in beverages using a data physicalisation with an irrelevant shape such as cubes.*
3. *Representing the beverages with a data physicalisations whose shape resembles the actual drink vessels will help the participants to better remember their* ***recommended daily caffeine limit****, than representing the caffeine in beverages using a data physicalisation with an irrelevant shape such as cubes.*

Experiment

The design of the experiment follows the structure of previous studies [2], [5]. Participants filled out a short demographics questionnaire before the experiment, during the experiment the participants had to identify whether the beverages chosen for the experiment had a high, medium or low caffeine content. Next the participants were asked to guess what they think their RDCL is, using the beverages to represent it. The researcher then presented them with their actual RDCL calculated from the weight (which was provided in the demographics questionnaire), and helped them to accurately represent this using the beverages. To test memorability, participants complete a memorability test in the form of a questionnaire immediately after the interactions with the data physicalisation and again a week later, with the same questionnaire to record recall decay. The tasks used in the study were designed to encourage interactions with the physicalisation, which is an important advantage of physicalisations when comparing them to other forms of data representation [5].

Experiment Considerations

When designing the experiment, the original idea was to have an interactive system that displayed information via an active data physicalisation. The user would be able to explore the system and see the different amounts of caffeine in a selected number of drinks, categorising them in energy drinks, types of coffee, and types of teas. The system would also be able to show how many of each of those drinks the user would need to consume in order to reach their RDCL. The participant would stand on a scale, and the system would show the participant their RDCL as a number, but also stack on top of each other, the number of each drink that would need to be consumed to reach their RDCL. The users would then have been tested immediately after interacting with the physicalisation to see how much they remembered, then tested again a few weeks later. Due to the time constraints, it would not have been feasible to design, build and program the system in time, so this idea was abandoned.

Taking into consideration some of the claims made in the “PhysiKit” paper, the personalisation of the data was deemed an important factor to the study, so it was decided that the system should be able to be personalised by the participants.

The next idea, tried to make the previous idea more simple, by making use of an interactive table available through another research project at Middlesex University. To inform the users of how much caffeine was in each drink, the participant would place the drink onto the interactive table and the table would display the caffeine in mg. In order to add more interaction, fun and the personal element, the participant would stand on a digital scale, and the RDCL of the participant would be calculated, and the participant would have been asked to place the number of drinks they think would be equivalent to their RDCL. The interactive table would have scanned a code at the bottom of the drink and calculated how much caffeine was being represented on the table. When the amount of caffeine represented on the table matched the RDCL, a green light would light up. Again, this idea was abandoned due to time constraints.

After that, the decision to step away from active data physicalisations was made, and the focus became more about getting the participant to interact more with the physicalisation. To keep things within the timeframe, the decision was made to stick with a static data physicalisation and the previous idea, simplified.

When thinking about some of the benefits of data physicalisations, being able to physically handle the data seemed like a big benefit. Some initial research was done into the effect of participants physically handling and interacting with the physicalisations and the possible benefits of this. A gap was noticed and the decision was made to investigate further into the benefits of physically handling physicalisation, specifically the effect of the shape of the physicalisation.

Design Considerations

The decision was made to use colour coding as the means of displaying the caffeine data because it is simple, quick to understand and is not novel to the participants, as colour coding is used in many aspects of every day life (e.g. traffic lights, strength of a tea, severity of a bruise, etc). The various shades were chosen because the brown could easily be linked back to coffee beans and general conceptions of caffeine. It was important for the data encoding to be something simple and familiar, so that the data encoding would not distract from the main focus, which was the shape of the physicalisation. This freed up the space to investigate only the effect of the shape of the physicalisations.

Every beverage was chosen because they each had distinct shapes and an assumption was made that the users that regularly drink those drinks and even those that don't consume caffeine regularly, would be able to easily recognise and distinguish the drinks. The specific shapes of the beverages also helped to set a distinction between each beverage and it allowed the drinks to be as closely connected to the original drinks consumed by the participants. Cube shaped blocks were used as the counterparts for the beverage vessels because they are very distinct from beverage vessels, and are not thought to be instinctively associated with drinks or caffeine.

Some thought went into finding ways to make the participants have to physically interact with the physicalisation and so interactive tasks were formulated. The simple design of the physicalisation and the tasks chosen enabled there to be more focus on the physical handling of the physicalisation, rather than the novelty of an active data physicalisation. Memorability was chosen as the object of testing, as it can be tested relatively simply, and a project like this would fall within the time frame.

Pilot Study

Before a pilot test was done, an initial quiz was sent out, asking participants about their general knowledge of caffeine. The task was to rank 24 different caffeinated drinks in order from least caffeine to most amount of caffeine. This was done to see if possible participants already knew the information that would be shared in the experiment. It was found that most participants of that quiz did not have a good grasp of how much caffeine was actually in many of the drinks listed.

An initial pilot test was done to quickly see any major faults in the way the experiment was done. The main changes after this was to move the questionnaire from paper to an online questionnaire, some initial errors spotted in the questions, and the demographic questions shortened.

Another pilot test of the experiment and the following questionnaires was done to see if the process of the experiment was easy to follow, if the questions in the questionnaire were understandable, and if the number of questions was appropriate and not too many. From this pilot test, the script for the examiner was refined, making the instructions clearer and more uniform. The questionnaire questions as well as the interview questions were also tweaked and made clearer.

User Demographics & Participants

There were 34 participants in total, 20 males and 14 females. As an incentive, participants were rewarded with snacks at the end of their interaction with the physicalisation. The participants were 18 - 59 years old, with an average age of 27.5 years old. This was a between-subjects study. The participants came from a range of backgrounds and were all fellow students and staff members of the Science and Technology Faculty at Middlesex University. User demographics were taken before the day of the experiment and this information was used to decide which group each participant was put into. The groups were made, making sure that the average age in each group was similar and that there was a similar male to female ratio. This was done to make sure that the age and sex of participants did not come to play in the results. The demographic data collected were: name, age, gender, weight and email address. The two groups the participants were put in are referred to as the *Real* group, and the *Cube* group, representing the two conditions in the study. The demographic results can be found in Appendix A.

Study Settings

Data

For this study, Caffeine was the chosen data topic, as it is one of the most consumed drinks in the world [27]–[29], so the participants are likely to be interested in it. The chosen drinks are some of the most sold caffeinated drinks in the UK [30] and each drink is distinctive in shape. During the experiment, the participants learned about the caffeine content in various drinks and what their Recommended Daily Caffeine Limit (RDCL) is, which is based on their weight. This could potentially be useful health information. The RDCL is given in mg, but also as the type and number of drinks that is roughly equivalent to their RDCL. Throughout the experiment, the total amount of caffeine in each drink was used, not the amount per unit volume (concentration). The amount of caffeine in a drink and the RDCL per weight was taken from [31].

Physicalisation

In a previous study, Stusac, et al, reported that very few participants found actually creating the data physicalisation useful as it did not encourage them to really think about the data they were physicalising, [5], therefore the physicalisation for this experiment was premade, as shown in Figure 1. The wooden blocks and drinks were bought, the blocks were hand painted, and the drinks were spray painted various colours to represent the amount of caffeine in each drink. However, S. Houben et al, reported that the participants in their study enjoyed the process of personalising the data, and it helped them to better connect with and understand the data [14]. So the idea of personalising physicalisations was implemented in this study. Participants were asked to put together their data physicalisation, and personalise the physicalisation by choosing the drinks that they would most likely drink.

Figure 7 - Painted wooden blocks used in Task 2 (top) and the unpainted wooden blocks used in Task 1 (bottom)

Cubes were used for the condition with unrelated shape. All the cubes were of the same size (around 7 x 7 x 7 cm) and were made from wood. The set of blocks used in the first part of the experiment retained their original wooden grain color (Figure 7 - bottom), so that the color grouping would not give away the answers to the task. After Task 1, the participants were given painted wooden blocks of the same size. The wooden blocks were painted, light brown, medium brown or dark brown, depending on which drink each cube represented (Figure 7 - top). The cubes were used by the *Cube* group.

Figure 8 - Painted beverage vessels used in Task 2 (top) and the unpainted beverage vessels used in Task 1 (bottom)

The condition with relatable shape, used the original unopened beverage vessels in the first part of the experiment as shown in Figure 8 - bottom, (again, so that the color grouping would not give away the answers to the task). After Task 1, the participants were given the same unopened beverage vessels, but they had all been spray painted light brown, medium brown or dark brown (Figure 8 - top). The beverage vessels were used by the *Real* group.

All drinks and blocks were labelled with the name of the drink it represented for easy identification. For both the cubes and the original beverage vessels, a dark brown was used for beverages with a High caffeine content, a medium shade of brown was used for beverages with a Medium caffeine content group and finally, a light brown was used for beverages with a low caffeine content.

Study Setup

The experiment was conducted in a small, isolated room with just the researcher and participant. A table was used as a working space for the participants to arrange the beverages (as shown in Figure 9, FIgure 10, Figure 11 and Figure 12), and a laptop was used to show the participants the instructions for each task. The laptop was also used by the participant to fill out the first questionnaire.

Procedure

Briefing

The participants were given a briefing about the experiment before the study started, stating that they would be given a few simple tasks including a sorting question, that they would be looking at common caffeinated drinks and that they would be asked about their caffeine habits. They were also informed that one of the tasks involved trying to figure out their RDCL which was the reason that their weight was needed. They were told that they would be given a short questionnaire to do and would have a quick semi-structured interview. The participants were not given any practice runs before the experiment.

Task 1: Rating Caffeinated Beverages

The first task was to group the drinks by the amount of caffeine they contained. They were asked to physically arrange them into three different groups: High Caffeine, Medium Caffeine and Low Caffeine (as shown in Figure 9 and Figure 10). Both the blocks and the beverage vessels had a label on them to help indicate which drink was being represented. At the end of the task, the participant was shown which drinks they got wrong, and was then shown the correct grouping. The participants had to use their own prior knowledge to complete this task.

Depending on the group the participant was in, they were given either 9 wooden cubes (Figure 9) or 9 beverage vessels (Figure 10), representing the 9 different drinks in the study. The original manufactured labels with the nutritional information that came with the bottles were left on the bottles so that each drink could be easily identified and so that they retained an authentic look. However, the participants in the Real group were instructed to not read the nutrition information that came with the bottles, this was to ensure that they were guessing the ratings of the beverages without any external help that the Cube group did not get. The total amount of caffeine in each drink is what was used during the study, not the amount per unit volume.

Table 1 was shown to the participants during this task.

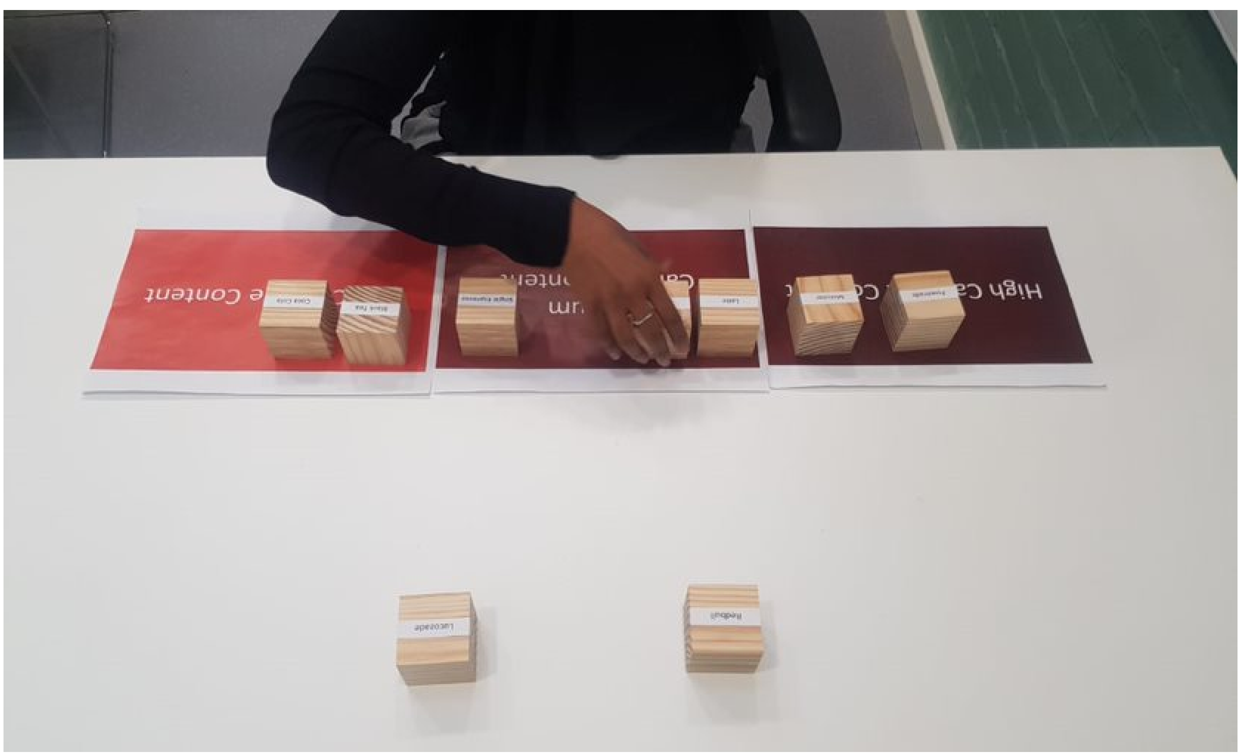

Figure 9 - Task 1 - Participant sorting the unpainted wooden blocks into low, medium and high caffeine content (left to right)

Figure 10 - Task 1 - Participant sorting the unpainted beverage vessels into low, medium and high caffeine content (left to right)

Name	**Caffeine (mg)**
High Caffeine Content	100 – 180
Medium Caffeine Content	80 - 100
Low Caffeine Content	30 - 50

Table 1: Grouping of the Low, Medium and High Caffeine content

Ranking	**Name**	**Caffeine (mg)**
1	Coffee	186
2	Monster Energy Drink	160
3	Powerade Fuel +	101
4	Single Espresso	92
5	Latte	92

7	Redbull Energy Drink	80
11	PG Tips Black Tea	50
12	Lucozade Energy Drink	46
13	Coca Cola	34

Table 2: Amount of caffeine (in *mg*) in each beverage

Task 2: Guessing RDCL

Showing average consumption of caffeine in a day

The second task was for participants to represent their current daily caffeine intake. The participant was given the painted set of blocks as shown in Figure 11, or the painted set of beverage vessels if they were in the Real group as shown in Figure 12. Each block or beverage was painted either light brown, medium brown or dark brown, representing Low Caffeine, Medium Caffeine and High caffeine respectively. The participant was asked to use this set of drinks to show the researcher how many of each drink they consumed on an average day, if any. The result would look similar to Figure 11 and Figure 12. If the participant drank more than one of a particular beverage in a day, the researcher could supply the participant with as many of each drink as they needed. For example, if the participant usually had 4 cups of coffee in a day, the researcher gave them 3 more coffee cups to physically represent this. If the drinks the participant would normally drink were not included in the selection, the participant was asked to use the drinks they would most likely drink out of the selection available. For example, if the user only drinks Carabao Energy drink, they were encouraged to use a Monster Energy drink instead.

Guessing RDCL

The participants were told what RDCL is and were asked if they had heard of this term before. They were then asked to guess what they think their personal RDCL is according to their weight. They were instructed to use the drinks to represent this amount, making sure to use only the drinks that they would most likely drink (Figure 11 and Figure 12). Again, they were shown Table 1, to help them have an idea of the range of caffeine in each drink. For example, if they thought that their RDCL is around 300*mg*, and they only drink Americano coffee, they were to choose two coffee cups (representing an Americano) to represent this, assuming that each Americano coffee contains about 150mg caffeine. At this point, the participants still had the painted blocks or beverage vessels in front of them.

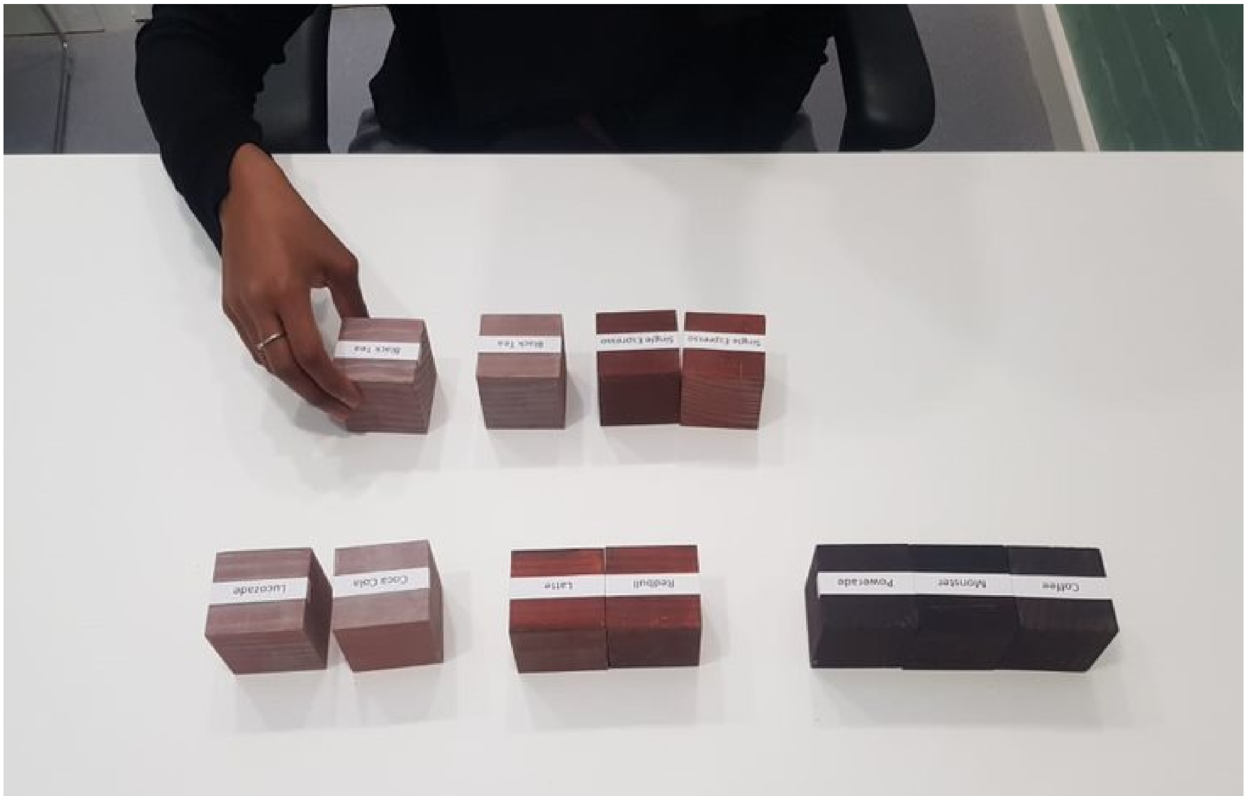

Figure 11 - Task 2 - Participant showing the researcher how much they think their RDCL is using the the painted wooden blocks

Figure 12 - Task 2 - Participant showing the researcher how much they think their RDCL is using the painted beverage vessels

This task was repeated after the participant was informed of what their actual RDCL range in *mg* was, (e.g. 456-481mg for someone with a weight of 79kg). They were asked to represent this newly presented RDCL, again using the drinks. After this, the researcher and participant went through the answer, adjusting the selected drinks where necessary to get an answer closest to their actual RDCL range using the actual amount of caffeine in each drink. Before this point, the participant was not informed of the actual amount of caffeine in each drink.

Immediate Questionnaire

Once the RDCL part was completed, and the participant was happy with the physical representation of their RDCL, the table was cleared and they were asked to fill out an online questionnaire to test how much they remembered from the experiment. The questionnaire consisted of 3 questions.

Question 1: *In which caffeine group does each beverage belong to?* Participants had to drag and drop the beverage names into the correct groups (high, medium and low caffeine).

Question 2: *What is your Recommended Daily Caffeine Limit range in mg?* Whilst answering this question, the researcher made it clear that participants were to try to remember both numbers in the range, but if they could not remember this, then they were to put what they could remember.

Question 3: *At the end of the session, during the last task, how many of each drink did you choose to represent your actual Recommended Daily Caffeine Limit?* Participants had to place a number next to each drink, showing how many of each drink they needed to fully represent their RDCL. This is a repeat of the RDCL task they did.

Semi-structured Interview

After the questionnaire, the participant was interviewed by the researcher. The questions included were:

1. *Did you find it difficult to understand the type of drink with the labels on the block/beverage container?*
2. *Was it easy to understand the amount of caffeine in each block/drink?*
3. *Did you find anything difficult today? If yes, why?*
4. *Did you learn anything today that you find important or surprising? If yes, why?*
5. *Is there anything that you felt you know already?*
6. *Is there anything else you would like to add?*
7. *Would anything that you've learned today affect your future caffeine choices?*

Some follow up questions were asked if further insight or understanding was needed.

Delayed Questionnaire

One week after their experiment session, participants were sent an email with a link to the last online questionnaire, which was a replica of the first questionnaire they completed. They were instructed to fill in the questionnaire within 24 hours of when the link was sent to them.

Data Collection & Data Processing

The participants were assessed based on the two memorability tests that were given on the day of their experiment and a week later. For the two memorability tests, we call them the *Immediate* and the *Delayed* questionnaire respectively. During the discussion, we refer to the two conditions in the study as the *Real* and the *Cube* group. Each participant had a memorabilty score calculated for each question, which compares the difference between answers given in the Immediate and Delayed questionnaires.

For Question 1, for each drink the participant got correct, they received 1 mark. The maximum mark a participant could receive is 9.

For Question 2, while the amount of RDCL is given as a range, and the question specifically asked for a range as an answer, some participants only provided a single value when answering this question in the memorability test. To accommodate this, the average value of the correct RDCL range is used. Instead of simply marking the answer as correct or wrong, we calculated the difference between the average of the recommended value and the average of the participants' answer. This was to measure how accurate an answer is, rather than the participant being either right or wrong, therefore the larger the difference, the less accurate the answer.

$$\frac{average\ of\ recommended\ value - average\ of\ user\ answer}{average\ of\ recommended\ value} \times 100\%$$

For Question 3, the accuracy is calculated as the percentage of the number of correct drinks out of the union of the drinks from the correct answer and what the participant answered. The reason for this is that sometimes participants would introduce drinks that are not part of the correct answer. The accuracy of the answer to Question 3 is calculated as:

$$Accuracy = \frac{A \cap B}{A \cup B}$$

where *A* is the number of each type of drink in the correct answer (such as two black teas and three latte coffees), *B* is the number of each type of drink in the participants' answer. This formula considers not only how many correct drinks an answer has but also the number of incorrect drinks in the answer.

Example:

Correct Answer = 2 coffees, 1 latte

Delayed Questionnaire Answer = 3 lattes

$$C = \frac{A \cap B}{A \cup B} = \frac{1\ latte}{2\ coffees + 3\ latte} = \frac{1}{5}$$

Participants Score = ⅕ = 0.2

A memorability score for each question for both the *Immediate* and *Delayed* questionnaires was calculated. Below is the formula used for this:

$$memorability\ score\ =\ \left(\frac{(immediate\ answer - delayed\ answer)}{immediate\ answer}\right)\ x\ 100$$

Results

A t-test was used to compare performance of the Cube and the Real group; There are three questions in each questionnaire, and these are compared separately. We compared the result of the memorability score for each question of the *Immediate* and *Delayed* questionnaires with each group to see if there is any significant memory decay after one week. The Cube group was our base condition. The results gathered from the experiment and the questionnaires can be found in Appendix A - D.

Question 1:

Sorting the drinks into the correct groups (high, medium and low caffeine).

On average, the Cube group got 86.11% of answers correct for the *Immediate* Questionnaire, and the Real group got 93.21% correct. In the *Delayed* Questionnaire, the Cube group got 79.17% of answers correct, and the Real group got 80.86% correct.

The average memorability score for Cube Group was 6.60%, and for the Real Group was 13.36%. The smaller the memorability score, the better the group did, so on average, the Cube group had a smaller recall decay, so did better than the Real group. The t-test comparing the two memorability scores for the two groups had a p-value of 0.423. This leads us to believe that there is not enough evidence to suggest that there is any significant difference in recall decay between the Cube group and the Real group.

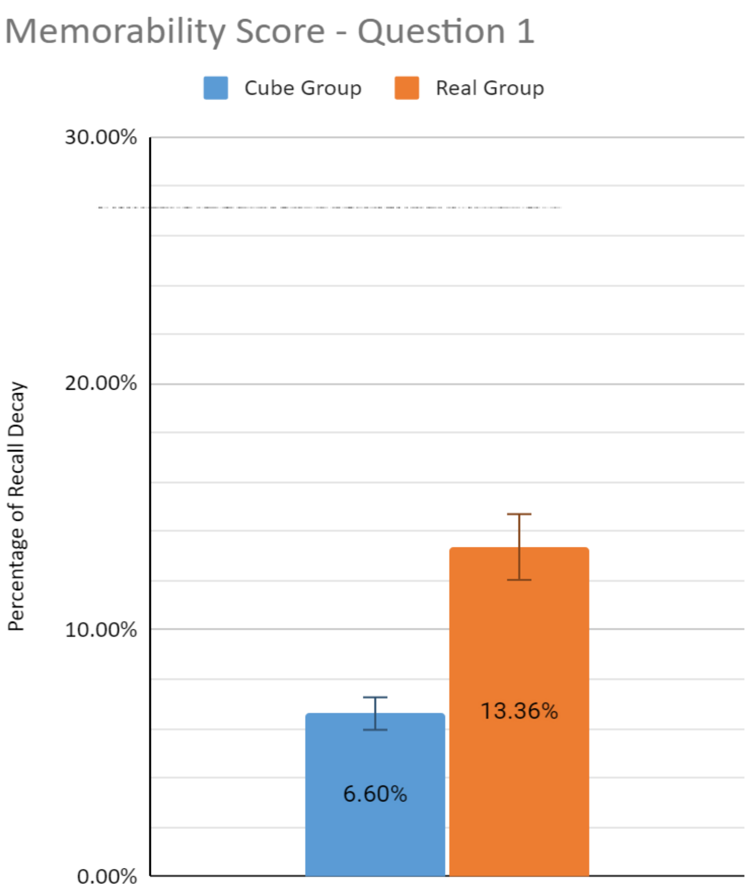

Figure 13 - Percentage of correct answers scored in Question 1 by both groups

The results gathered from the questionnaires for Question 1 can be found in Appendix B.

Question 2:

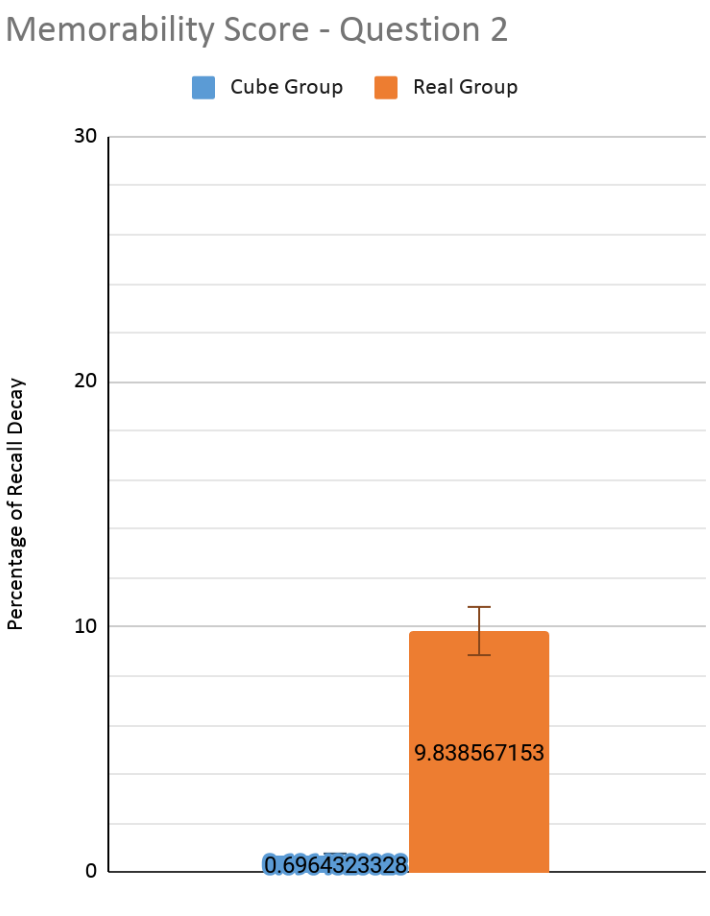

Figure 14 - Percentage of correct answers scored in Question 2 by both groups

Asking the participants to remember their RDCL in *mg*.

On average, the Cube group were 2.16% away from their correct answer in the *Immediate* questionnaire, and their Real group were 0.55% away from the correct answer. For the *Delayed* questionnaire, the Cube group were 2.86% away from their correct answer, and the Real group were 10..38% away from their correct answer.

The average memorability score for Cube Group was 0.695%, and for the Real Group was 9.839%. The smaller the memorability score, the better the group did, so on average, the Cube group had a smaller recall decay, so did better than the Real group. The t-test comparing the two memorability scores for the two groups had a p-value of 0.940. This leads us to believe that there is not enough evidence to suggest that there is any significant difference in recall decay between the Cube group and the Real group.

The results gathered from the questionnaires for Question 2 can be found in Appendix C.

Question 3:

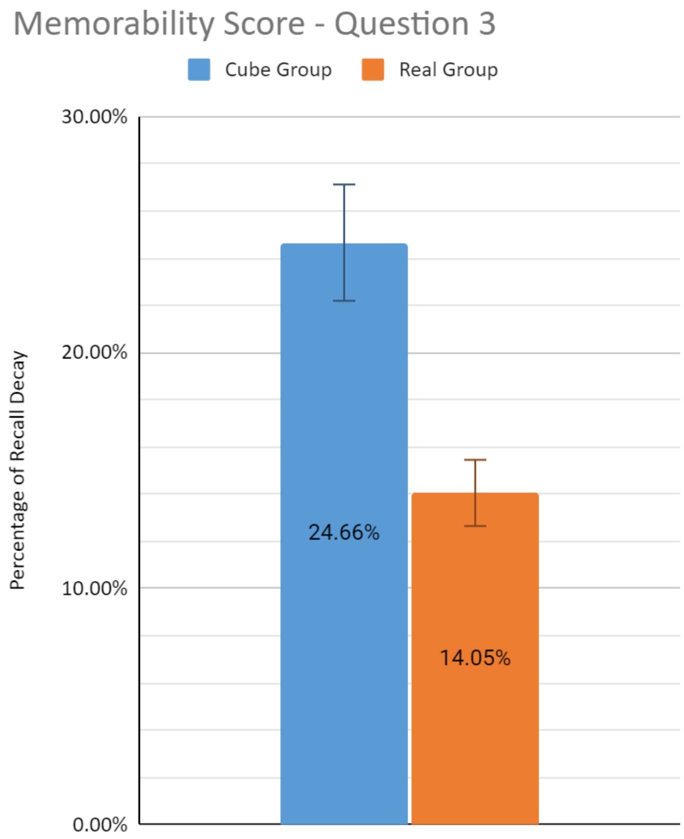

Figure 15 - Percentage of correct answers scored in Question 3 by both groups

Asking the participants to remember their RDCL in terms of the number of units for different drink types.

On average, the Cube group got 95.20% of answers correct for the *Immediate* Questionnaire, and the Real group got 97.53% correct. In the *Delayed* Questionnaire, the Cube group got 71.78% of answers correct, and the Real group got 83.73% correct.

The average memorability score for Cube Group was 24.66%, and for the Real Group was 14.05%. The smaller the memorability score, the better the group did, so on average, the Real group had a smaller recall decay, so did better than the Cube group. The t-test comparing the two memorability scores for the two groups had a p-value of 0.250. This leads us to believe that there is not enough evidence to suggest that there is any significant difference in recall decay between the Cube group and the Real group.

The results gathered from the questionnaires for Question 3 can be found in Appendix D.

In summary, the t-tests showed no significant difference between the two conditions as the p-values calculated are above the significance level.

Participants Feedback

When asked about their understanding of the physicalisation (during the interview), all participants claimed to fully understand how the physicalstion worked. Participants also claimed to fully understand the data that was presented to them, however, some participants required extra explanation to reach full understanding of how the physicalisation worked and the categorisation of the data. Several participants also commented that being able to see the blocks and beverage vessels laid out in their groups on the table helped them to remember the data. Participants commented that being able to physically place the items in the different positions on the table themselves helped them to understand and remember the data. Many comments were also made that the colour coding of the drinks helped in remembering the data and the groupings of the drinks. Most of the participants did not know what RDCL was or how it was calculated, although around 50% of the participants had heard of RDCL before.

Discussion

From the data gathered, there is not enough evidence to suggest that changing the shapes of the physicalisations make a difference in the recall ability of the user, thus disproving both hypotheses.

The results from this experiment suggest that creating physicalisations that actively resemble the data topic, does not necessarily help the user remember the information given to them through the physicalisation. It does, however, also suggest that creating physicalisations that do not actively resemble the data topic, will not make it harder for the user to remember the information given to them through the physicalisation.

Cubes and similar shapes are more often used to represent data (such as bar charts), than beverage vessels, even when representing beverage related data. It is possible that the familiarity of the cube representation had as great an effect on the users recall ability, as the more literal representation of the beverage vessels. as most participants in both groups did not report any trouble understanding the data but rather said that they fully understood the data.

Another suggestion for this finding is that the data that the participants explored was relatively simple, and so it could be that as long as the data and tasks are simple, the shape of the physicalisation does not further add to the recall ability of the user.

When asked about their understanding of the physicalisation and the data given, all participants understood the data and the physicalisation, however some claimed to not fully understand until further explanation on how the categorisation of the drinks worked. Several participants commented that physically placing the drinks in the different positions on the table helped them to understand and remember the data. Participants also commented that being able to see the blocks and beverage vessels laid out in their groups on the table helped them to remember the data. Many comments were also made that the colour coding of the drinks helped them to remember the data and groupings of the drinks. Most of the participants did not know what RDCL was or how it was calculated, although around 50% of the participants had heard of RDCL before.

Percentage of Correct Answers						
	Q1		**Q2***		**Q3**	
	Immediate	**Delayed**	**Immediate**	**Delayed**	**Immediate**	**Delayed**
Cube	86.11	79.17	2.16	2.86	95.2	71.78
Real	93.21	80.86	0.55	10.38	97.53	83.73

Table 3 - Percentage of correct answers scored for all three Questions

*For Question 2, the percentages reflect how far away from correct answer the participants were, so the smaller the number the better the participants did.

As expected, participants experienced a recall decay after a week, however, the participants on average scored very well in both questionnaires, so the recall decay was small. This general understanding and high scores may be due to the simplicity of the tasks and questions, but also how few tasks and questions there were, may have impacted the results. During the interview stage after the questionnaires, the participants all claimed to fully understand both the data and the tasks. A suggestion for this, particularly for Question 3, is the amount of time taken by the researcher to make sure that the participants fully understood each task and how the data physicalisations worked. This is because there was no time limit for each task so the researcher and participants spent as much time as was needed to make sure that the participant understood how the task and the physicalisation worked. Also the time spent with the participants to come up with the final representation of each participant's RDCL during the interaction with the physicalisation in the final task was often the longest part of the experiment process. This section also often required a lot of arranging and rearranging of the beverages so there often was a lot more interaction that happened, thus possibly helping the participants to better understand and remember the answers. Some participants did better in the delayed condition, however this is likely to be down to chance and the participants guessing the correct answers..

Conclusion and Further Works

The investigation into the effect of directly relatable shape versus a more abstract shape of data physicalisation on recall ability, resulted in an insignificant difference between the two conditions. Thus, we did not find enough evidence to suggest that creating a physicalisation that actively resembles the data topic, makes a difference in the recall ability of the user. Previous studies have shown that data physicalisations can help improve recall ability. We conjecture that if the data and task are relatively simple (as in this study), the shape of the physicalisation does not further add to the recall ability.

Further work would involve research into the effects of a data physicalisation's shape with more complex data and/or more difficult tasks. This study can be repeated with more complex data and a different set of tasks to check if data complexity and task difficulty can influence the impact of data physicalisation shape. Further investigations can also look into the effect of relatable shape versus abstract shape on the longer-term recall ability.

It will also be an interesting study to explore the effect of other aspects of abstractness of physicalisation on the recall ability of the participant, for example multiple levels of shape abstraction in data physicalisation (there are only two levels in this study) if it is shown that the shape of data physicalisation does have an effect on memorability or other analysis-related metrics.

References

[1] Y. Jansen *et al.*, ‘Opportunities and Challenges for Data Physicalization’, in *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, Seoul, Republic of Korea, Apr. 2015, pp. 3227–3236. doi: 10.1145/2702123.2702180.

[2] S. Stusak, J. Schwarz, and A. Butz, ‘Evaluating the Memorability of Physical Visualizations’, in *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, Seoul, Republic of Korea, Apr. 2015, pp. 3247–3250. doi: 10.1145/2702123.2702248.

[3] ‘Evaluating the Efficiency of Physical Visualizations’, in *Proceedings of the 2013 Annual Conference on Human Factors in Computing Systems*, Paris, France, Apr. 2013, p. Pages 2593-2602. Accessed: Jan. 30, 2020. [Online]. Available: https://dl.acm.org/doi/abs/10.1145/2470654.2481359

[4] W. Bevan and J. A. Steger, ‘Free Recall and Abstractness of Stimuli’, *Science*, vol. 172, no. 3983, p. 597, May 1971, doi: 10.1126/science.172.3983.597.

[5] S. Stusak, M. Hobe, and A. Butz, ‘If Your Mind Can Grasp It, Your Hands Will Help’, in *Proceedings of the TEI ’16: Tenth International Conference on Tangible, Embedded, and Embodied Interaction*, Eindhoven, Netherlands, Feb. 2016, pp. 92–99. doi: 10.1145/2839462.2839476.

[6] D. Kerzel, ‘Visual short-term memory is influenced by haptic perception.’, *J. Exp. Psychol. Learn. Mem. Cogn.*, vol. 27, no. 4, pp. 1101–1109, 2001, doi: 10.1037/0278-7393.27.4.1101.

[7] L. M. Triona and D. Klahr, ‘Point and Click or Grab and Heft: Comparing the Influence of Physical and Virtual Instructional Materials on Elementary School Students’ Ability to Design Experiments’, *Cogn. Instr.*, vol. 21, no. 2, pp. 149–173, Jun. 2003, doi: 10.1207/S1532690XCI2102_02.

[8] F. Amini, S. Rufiange, Z. Hossain, Q. Ventura, P. Irani, and M. J. McGuffin, ‘The Impact of Interactivity on Comprehending 2D and 3D Visualizations of Movement Data’, *IEEE Trans. Vis. Comput. Graph.*, vol. 21, no. 1, pp. 122–135, Jan. 2015, doi: 10.1109/TVCG.2014.2329308.

[9] F. Taher, Y. Jansen, J. Woodruff, J. Hardy, K. Hornbæk, and J. Alexander, ‘Investigating the Use of a Dynamic Physical Bar Chart for Data Exploration and Presentation’, *IEEE Trans. Vis. Comput. Graph.*, vol. 23, no. 1, pp. 451–460, Jan. 2017, doi: 10.1109/TVCG.2016.2598498.

[10] M. Hohl, ‘From abstract to actual: art and designer-like enquiries into data visualisation’, *Kybernetes*, vol. 40, no. 7/8, pp. 1038–1044, Jan. 2011, doi: 10.1108/03684921111160278.

[11] ‘Tide - Luke Jerram’. https://www.lukejerram.com/tide/ (accessed Dec. 14, 2020).

[12] K. A. Pyburn, ‘Review of Material Culture and Mass Consumption; The Ethnoarchaeology of Refuse Disposal’, *J. Field Archaeol.*, vol. 19, no. 2, pp. 230–232, 1992, doi: 10.2307/529987.

[13] S. Ross, ‘The Comfort of Things - By Daniel Miller’, *Br. J. Sociol.*, vol. 60, pp. 841–3, Dec. 2009, doi: 10.1111/j.1468-4446.2009.01277_6.x.

[14] S. Houben *et al.*, ‘Physikit: Data Engagement Through Physical Ambient Visualizations in the Home’, in *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems - CHI ’16*, Santa Clara, California, USA, 2016, pp. 1608–1619. doi: 10.1145/2858036.2858059.

[15] ‘Physikit: Data Engagement Through Physical Ambient Visualizations in the Home - YouTube’. https://www.youtube.com/watch?v=H2jDpMY29aE&ab_channel=StevenHouben (accessed Dec. 14, 2020).

[16] R. A. Khot, F. ‘Floyd’ Mueller, and L. Hjorth, ‘SweatAtoms: materializing physical activity’, in *Proceedings of The 9th Australasian Conference on Interactive Entertainment: Matters of Life and Death*, New York, NY, USA, Sep. 2013, pp. 1–7. doi: 10.1145/2513002.2513012.
[17] M. A. Borkin *et al.*, ‘What Makes a Visualization Memorable?’, *IEEE Trans. Vis. Comput. Graph.*, vol. 19, no. 12, pp. 2306–2315, Dec. 2013, doi: 10.1109/TVCG.2013.234.
[18] ‘ISOTYPE Visualization | Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems’. https://dl.acm.org/doi/10.1145/2702123.2702275 (accessed Jul. 17, 2021).
[19] E. Tufte, ‘The Visual Display of Quantitative Information / E.R. Tufte.’, *Am. J. Phys.*, vol. 31, Jan. 2001, doi: 10.1109/MPER.1988.587534.
[20] H. Li and N. Moacdieh, ‘Is “chart junk” useful? An extended examination of visual embellishment’, *Proc. Hum. Factors Ergon. Soc. Annu. Meet.*, vol. 58, no. 1, pp. 1516–1520, 2014, doi: 10.1177/1541931214581316.
[21] S. Bateman, R. L. Mandryk, C. Gutwin, A. Genest, D. McDine, and C. Brooks, ‘Useful junk?: the effects of visual embellishment on comprehension and memorability of charts’, in *Proceedings of the 28th international conference on Human factors in computing systems - CHI ’10*, Atlanta, Georgia, USA, 2010, p. 2573. doi: 10.1145/1753326.1753716.
[22] P. Parsons and P. Shukla, ‘Data Visualization Practitioners’ Perspectives on Chartjunk’, in *2020 IEEE Visualization Conference (VIS)*, Oct. 2020, pp. 211–215. doi: 10.1109/VIS47514.2020.00049.
[23] U. H. Syeda and J. Raynor, ‘Evaluating the Effects of Visual Embellishments and Context on Comprehension, Recall and Preference of Charts’, Nov. 2020, Accessed: Jul. 24, 2021. [Online]. Available: https://osf.io/d3kex
[24] T. F. Brady, T. Konkle, and G. A. Alvarez, ‘A review of visual memory capacity: Beyond individual items and toward structured representations’, *J. Vis.*, vol. 11, no. 5, pp. 4–4, May 2011, doi: 10.1167/11.5.4.
[25] F. Chevalier, R. Vuillemot, and G. Gali, ‘Using Concrete Scales: A Practical Framework for Effective Visual Depiction of Complex Measures’, *IEEE Trans. Vis. Comput. Graph.*, vol. 19, no. 12, pp. 2426–2435, Dec. 2013, doi: 10.1109/TVCG.2013.210.
[26] F. Taher *et al.*, ‘Exploring Interactions with Physically Dynamic Bar Charts’, in *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, Seoul, Republic of Korea, Apr. 2015, pp. 3237–3246. doi: 10.1145/2702123.2702604.
[27] E. Fitt, D. Pell, and D. Cole, ‘Assessing caffeine intake in the United Kingdom diet’, *Food Chem.*, vol. 140, no. 3, pp. 421–426, Oct. 2013, doi: 10.1016/j.foodchem.2012.07.092.
[28] C. M. Reyes and M. C. Cornelis, ‘Caffeine in the Diet: Country-Level Consumption and Guidelines’, *Nutrients*, vol. 10, no. 11, Nov. 2018, doi: 10.3390/nu10111772.
[29] C. Ágoston, R. Urbán, O. Király, M. D. Griffiths, P. J. Rogers, and Z. Demetrovics, ‘Why Do You Drink Caffeine? The Development of the Motives for Caffeine Consumption Questionnaire (MCCQ) and Its Relationship with Gender, Age and the Types of Caffeinated Beverages’, *Int. J. Ment. Health Addict.*, vol. 16, no. 4, pp. 981–999, 2018, doi: 10.1007/s11469-017-9822-3.
[30] Statista Research Department, ‘Leading brands of energy drinks in the UK 2018’, Sep. 25, 2020. https://www.statista.com/statistics/308493/leading-brands-of-energy-drinks-excluding-colas-or-mixers-for-alcoholic-drinks-in-the-uk/ (accessed Jan. 25, 2020).
[31] ‘Caffeine Safe Limits: Calculate Your Safe Daily Dose’, *https://www.caffeineinformer.com/*. https://www.caffeineinformer.com/caffeine-safe-limits (accessed Jan. 31, 2020).

Appendix A

Demographic information collected from participants, and their answers during the experiment

Age	M/F	Weight *(kg)*	Real RDCL *(mg)*	Task 1	Task 2				
				No.of wrong answers	Average caffeine in a day	Knew RDCL before	Participant guess of RDCL	Version 2 of RDCL	Final RDCL
32	M	79	456-481	2	1 Latte, 1 Coffee, 1 Espresso	Yes	1 powerade, 1 Monster	1 powerade, 1 monster, 1 coffee	2 coffee, 1 latte
28	M	88	517-547	5	3 cokes, 1 coffee, 1 tea	No	1 tea	3 coffees, 1 tea, 5 cokes	5 cokes, 2 coffees
24	M	69	396-420	4	2 latte	Yes	2 latte	4 latte	4 lattte, 1 espresso
24	M	85	487-511	4	1 coke, 1 redbull, 1 coffee	No	1 redbull	4 lucozades, 4 cokes, 1 redbull	4 lucozade, 4 cokes, 2 redbulls
20	M	55	306-330	5	1 coke	No	1 tea, 1 coke	4 teas, 4 cokes	4 teas, 3 cokes
21	F	50	276-300	6	2 Latte	Yes	1 Latte	1 Latte, 1 coffee	2 Lattee, 1 Espresso
42	F	63	366-390	6	5 coffee, 3 tea	Yes	2 coffee, 2 tea	2 coffee, 1 tea	2 coffee
31	F	70	396-420	5	3 coffees	No	2 coffees	2 coffees, 1 coke	2 coffees, 1 coke
26	F	59	330-360	4	3 coke, 2 redbull	No	2 coke, 1 redbull	3 coke, 2 redbull	4 coke, 2 redbull, 1 lucozade
18	F	63	366-390	5	1 tea	Yes	1 Tea	5 teas, 1 latte	5 teas, 1 coke, 1 latte
28	M	96	577-601	4	None	No	1 lucozade	5 cokes, 5 lucozades	5 cokes, 4 lucozades, 1 redbull, 1 monster
30	M	62	366-390	4	None	No	1 powerade, 1 lucozade	2 lucozades, 1 redbull, 1	4 lucozades, 1 redbull, 1

								powerade	powerade
23	F	101	607-631	5	None	Yes	1 redbull, 1 coke	2 monsters, 2 redbull	3 monsters, 2 redbull
19	F	60	330-360	6	2 teas	No	2 teas, 1 cokes, 1 latte	2 teas, 2 lattes, 1 coke	2 teas, 2 lattes, 2 cokes
27	M	72	426 - 450	5	2 espresso	Yes	2 espresso	4 espresso, 1 coke	4 espresso, 2 coke
49	M	75	426 - 450	2	2 espressos, 2 teas	Yes	2 espresso, 2 coffee, 2 tea	2 espresso, 3 coffee, 2 tea	1 coffee, 2 espresso, 2 tea
35	F	58	330-360	5	3 coffees, 1 latte, 1 tea	no	1 coffee	1 tea, 3 coffees	1 coffee, 1 latte, 2 tea
39	M	92	547-571	5	2 coffees	No	1 espresso, 1 latte, 1 coffee	3 coffees, 1 espresso, 1 latte	2 lattes, 2 coffees
21	M	72	426-450	4	1 monster, 1 cofee, 2 espresso	No	1 monster, 1 cofee, 2 espresso	1 monster, 2 coffee, 2 espresso	1 coffee, 1 monster, 1 espresso
21	F	87	517-541	4	2 teas, 2 latte	No	1 tea, 1 latte	3 latte, 1 redbull, 1 tea, 1 lucozade, 1 coke	3 latte, 1 redbull, 2 tea, 1 lucozade, 1 coke
25	M	70	396-420	6	1 coffee, 1 coke	Yes	2 coffees, 1 coke, 1 tea	2 coffes, 1 tea, 1 coke, latte	2 coffees, 1 coke
59	M	79	456-481	2	1 tea	Yes	1 coke, 3 teas	5 teas, 2 cokes, 2 lucozades	5 teas, 3 lucozades, 2 cokes
42	M	70	396-420	6	1 coffee, 1 tea	No	2 coffee, 1 tea, 1 lucozade	2 coffee, 1 tea	2 coffee, 1 tea
23	F	62	366-390	7	1 coke, 1 latte	No	1 coffee, 1 latte	2 latte, 2 espresso	2 Latte, 2 espresso
20	F	56	330-360	6	None	No	1 coffee, 1 lucozade	1 coffee, 4 cokes, 2 lucozades	1 Coffee, 2 cokes, 2 lucozades
21	M	73	426-450	5	None	Yes	1 coffee, 1 powerade, 1	2 coffees, 1 powerade, 2	1 coffee, 1 powerade, 2

							coke, 1 lucozade	lucozades, 1 coke	lucozade, 2 coke
23	M	69	396-420	5	None	No	2 cokes	5 cokes, 3 lucozades	5 cokes, 3 lucozades, 1 powerade
18	F	59	330-360	7	None	No	1 tea, 1 coke	1 powerade, 1 monster, 1 redbull	1 powerade, 1 monster, 1 redbull
21	M	68	396 - 420	5	1 powerade	No	1 monster, 1 powerade, 1 lucozade	2 monsters, 1 powerade, 1 lucozade	2 monsters, 1 powerade
25	M	95	547 - 571	4	5 coffees, 5 latte, 1 espresso, 2 redbull, 2 tea, 2 coke	No	1 coffee, 1 redbull	4 coffee	3 coffee, 1 coke
30	F	70	396 - 420	7	1 latte, 1 coke	Yes	2 latte, 1 coke	3 latte, 2 coke	4 latte, 1 coke
26	M	71	426 - 450	7	2 coffee	No	2 coffee	3 coffee	2 coffee, 1 espresso
21	F	50	276 - 300	2	2 Coffee, 1 latte	Yes	2 coffee, 1 latte, 1 monster, 1 redbull	1 coffee, 1 latte, 1 coke	1 coffee, 1 latte
28	F	57	330 - 360	5	2 tea	No	3 teas	4 teas, 3 cokes	5 teas, 3 cokes

Appendix B

Participants answers for Question 1

Group	Question 1 - Grouping Caffeinated Drinks				
	Experiment	Questionnaire 1		Questionnaire 2	
	(No. of Wrong answers)	Total Wrong	Total Right	Total Wrong	Total Right
Cube	2	0	9	2	7

Cube	5	2	7	0	9
Cube	4	2	7	2	7
Cube	4	0	9	2	7
Cube	5	0	9	2	7
Cube	6	2	7	0	9
Cube	6	5	4	4	5
Cube	5	0	9	0	9
Cube	4	0	9	0	9
Cube	5	0	9	3	6
Cube	4	0	9	2	7
Cube	4	4	5	7	2
Cube	5	2	7	2	7
Cube	6	3	6	2	7
Cube	5	0	9	0	9
Cube	2	0	9	2	7
Real	5	3	6	4	5
Real	5	2	7	0	9
Real	4	0	9	2	7
Real	4	0	9	0	9
Real	6	0	9	0	9
Real	2	0	9	2	7
Real	6	0	9	4	5
Real	7	2	7	5	4
Real	6	0	9	0	9
Real	5	0	9	0	9
Real	5	0	9	0	9
Real	7	0	9	5	2
Real	5	0	9	0	9

Real	4	0	9	0	9
Real	7	2	7	3	6
Real	7	0	9	0	9
Real	2	0	9	0	9
Real	5	2	7	4	5

Appendix C

Participants answers for Question 2

Group	Question 2 - Remembering Actual RDCL range in mg					
	Experiment		Questionnaire 1		Questionnaire 2	
	Actual RDCL (in mg)	Average of Correct Answer	Participants Answer	Average of Submitted Answer	Participants Answer	Average of Submitted Answer
Cube	456-481	468.5	400-480mg	460	350	350
Cube	517-547	532	540	540	480	480
Cube	396-420	408	396-420	219	390-425	407.5
Cube	487-511	499	487-511	499	500	500
Cube	306-330	318	306-330	318	302-336	319
Cube	276-300	288	276-280	278	276-280	278
Cube	366-390	378	360	360	300	300
Cube	396-420	408	396-420	408	380-450	415
Cube	330-360	345	330-360	345	320-360	340
Cube	366-390	378	360-390	375	360-390	375
Cube	577-601	589	550	550	570	570
Cube	366-390	378	330-360	345	180	180
Cube	607-631	619	638-687	797	600+	600
Cube	330-360	345	340-370	355	350	350
Cube	426 - 450	438	452	452	450	450
Cube	426 - 450	438	420-470	445	400	400
Real	330-360	345	300-360	330	360	360
Real	547-571	559	561 - 583	572	426-450	438
Real	426-450	438	426-520	473	130	130
Real	517-541	529	517	517	517	517
Real	396-420	408	390-430	410	380-420	400
Real	456-481	468.5	450 -480	465	480	480

Real	396-420	408	396-420	408	200	200
Real	366-390	378	368	368	360	360
Real	330-360	345	330-360	345	340-360	350
Real	426-450	438	426-510	468	420-520	470
Real	396-420	408	396	396	350	350
Real	330-360	345	310-360	335	300	300
Real	396 - 420	408	370-416	393	416	416
Real	547 - 571	559	577-601	589	577-601	589
Real	396 - 420	408	390-410	400	400	400
Real	426 - 450	438	400-450	425	400-450	425
Real	276 - 300	288	268	268	270-300	285
Real	330 - 360	345	320-360	340	260	260

Appendix D

Participants answers for Question 3

Group	Question 3 - Remembering Final RDCL in terms of drinks		
	Experiment	**Questionnaire 1**	**Questionnaire 2**
Cube	2 coffee, 1 latte	2 Coffee, 1 Latte	3 Latte
Cube	5 cokes, 2 coffees	2 coffee, 5 cokes	2 Coffee 10 Cokes
Cube	4 latte, 1 espresso	4 latte, 1 espresso	4 Latte, 1 Espresso
Cube	4 lucozade, 4 cokes, 2 redbulls	4 cokes, 2 redbull, 4 lucozade	4 Cokes, 2 Redbulls, 4 Lucozades
Cube	4 teas, 3 cokes	3 cokes, 4 teas	4 cokes, 5 teas
Cube	2 Latte, 1 Espresso	2 latte, 1 espresso	2 Latte, 1 espresso
Cube	2 coffee	2 coffee	2 Coffee, 1 tea
Cube	2 coffees, 1 coke	2 Coffee, 1 Coke	2 Coffee, 1 Coke
Cube	4 coke, 2 redbull, 1 lucozade	4 cokes, 2 redbull, 1 lucozade	4 Coke, 2 Redbull, 1 Lucozade
Cube	5 teas, 1 coke, 1 latte	1 Coke, 1 Latte, 5 tea	1 Coke, 1 Latte, 5 Tea
Cube	5 cokes, 4 lucozades, 1 redbull, 1 monster	5 Cokes, 1 Redbull, 1 Monster, 4 Lucozade	10 Coke, 10 Lucozade
Cube	4 lucozades, 1 redbull, 1 powerade	1 Powerade, 1 Monster, 4 Lucozade	1 Redbull, 6 Lucozades
Cube	3 monsters, 2 redbull	2 redbull, 4 Monster	1 Redbull, 2 Monster
Cube	2 teas, 2 lattes, 2 cokes	2 Coke, 2 Latte, 2 Tea	2 Coke, 2 Latte, 2 Tea
Cube	4 espresso, 2 coke	2 Coke, 4 Espresso	1 Coke, 4 Espresso
Cube	1 coffee, 2 espresso, 2 tea	1 Coffee, 1 Tea, 2 Espresso	1 Coffee, 2 Tea, 1 espresso
Real	1 coffee, 1 latte, 2 tea	1 Coffee, 1 Latte, 2 Teas	1 Coffee, 3 Tea
Real	2 lattes, 2 coffees	2 coffee, 2 latte	2 Coffee, 2 Latte
Real	1 coffee, 1 monster, 1 espresso	1 coffee, 1 monster, 1 espresso	1 Coffee, 1 Latte, 1 Espresso

Real	3 latte, 1 redbull, 2 tea, 1 lucozade, 1 coke	1 coke, 1 redbull, 3 latte, 1 lucozade, 2 tea	1 coke, 1 Redbull, 3 Latte, 1 Lucozade, 2 tea
Real	2 coffees, 1 coke	2 coffee, 1 coke	2 Coffee, 1 Coke, 1 Tea
Real	5 teas, 3 lucozades, 2 cokes	3 cokes, 2 lucozade, 5 tea	3 Coke, 2 Lucozade, 5 Tea
Real	2 coffee, 1 tea	2 coffee, 1 tea	1 Coffee, 1 Lucozade
Real	2 Latte, 2 espresso	2 Latte, 2 Espresso	2 Latte, 2 Espresso
Real	1 coffee, 2 cokes, 2 lucozades	1 Cofffee, 3 Coke, 2 Lucozade	2 Coffee, 4 Cokes, 2 Lucozade
Real	1 coffee, 1 powerade, 2 lucozade, 2 coke	1 Coffee, 2 Cokes, 1 Powerade, 2 Lucozade	1 Coffee, 2 Coke, 1 Powerade, 2 Lucozade
Real	5 cokes, 3 lucozades, 1 powerade	5 Cokes, 1 Powerades, 2 Lucozade	5 coke, 1 Powerade, 2 lucozade
Real	1 powerade, 1 monster, 1 redbull	1 Powerade, 1 redbull, 1 monster	1 Powerade, 1 Redbull, 1 Monster
Real	2 monsters, 1 powerade	1 Powerade, 2 Monster	1 Powerade, 2 Monster
Real	3 coffee, 1 coke	3 Coffee, 1 Coke	3 Coffee, 1 coke
Real	4 latte, 1 coke	1 Coke, 4 latte	1 Coke, 4 Latte
Real	2 coffee, 1 espresso	2 Coffee 1 Espresso	2 Coffee, 1 Espresso
Real	1 coffee, 1 latte	1 Coffee, 1 Latte	1 Coffee, 2 Latte
Real	5 teas, 3 cokes	3 Coke, 5 Tea	4 Coke, 5 Tea