Tangibits: Multimodal communication of climate change data - exploring vibration, sound and temperature

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Abstract

Data physicalizations convey data through physical variables. Data physicalization research focuses on exploring novel methods on how to incorporate these physical variables for data communication. As an emerging field, empirical data concerning the impact physical variables have on data perception and user experience is lacking, especially when considering multimodal physicalizations.

This paper aims to evaluate the impact multiple physical variables: vibration, temperature, and sound, have on data perception and user experience, including combinations of these variables to evaluate a multimodal installation.

Data physicalizations require use case data, the decision was made to use climate change data for the installation. As it is a current issue with plenty of data and visualizations already existing, yet lacking multimodal installations. In the case of this research, the physicalization represents three climate change indicators: sea temperature, air temperature, and land precipitation, across 5 regions: Greenland, the North sea, the Indonesian sea, Antarctica, and the East Bering sea, in a timeframe from 1960 to 2090 using future climate change projections.

To evaluate the different modalities, a data physicalization was designed that allowed users to select a region, indicator, and year, users will then feel the data through either one or two of the modalities. Consequently, this data physicalization was evaluated on the basis of efficiency, accuracy, mental load and, subjective confidence through a between-subject user study involving 24 participants.

The results of the user evaluation showed no statistical significance to assume the modalities had an impact on the data perception and user experience. All modalities and combinations of modalities are assumed to be equal on the evaluated variables. Furthermore, no statistical significant evidence was found when comparing participants engaging with a single modality against participants engaging with a combination of modalities. To find whether there is truly no difference between modalities, it is recommended to repeat the study with a larger sample size.

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Chapter 1 – Introduction

Data physicalizations are installations that use physical variables to represent data. They allow for new ways to interact with data, as they can not only be seen but also perceived through the other senses. Research has identified multiple variables that could be used to represent the data in a multisensory way [3]. As a result, data physicalizations have been shown to have various benefits over data visualizations such as: cognitive benefits, including positively impacting perception of data and better recall of the data; enhancing emotional connection to the data, and leveraging haptic memory [4]. However, even though data physicalizations have many benefits, the research field has only recently started to grow. Currently, there is not yet much research evaluating the impact of combinations of multisensory data experiences created using different combinations of sensory modalities on accuracy and efficiency. The aim of this research is to evaluate combinations of haptic and sonic variables and thereby to find how the combinations compare in user experience and data perception using ordinal data. Specifically, vibration, sound, temperature will be evaluated in this research. To evaluate the different combinations, a use case of climate change data will be used to design the installation.

Earth's climate has been changing for over millions of years, due to natural factors such as changes in solar radiation, volcanic activity, and orbital cycles [1]. However, currently natural factors are not the only driver behind the changing climate as human influence has become one of the major drivers behind climate change [1]. The emissions of greenhouse gasses into the atmosphere by humans results in warming of the atmosphere, land, and ocean. Greenhouse gasses are also not the only human factors influencing the climate, actions such as urbanization, land use, and the emissions of aerosols also directly influence the changing climate. Due to these human factors, there is a potential that in 2300 the earth's global surface temperatures could be 2.3C-4.6C higher than 100 years ago. This would have disastrous consequences as with each increase of only a fraction of a degree, air pollution, disease, extreme weather events, forced displacement, food insecurity, and mental health will only get worse [2].

The goal of the research is to answer the research question: **How do different combinations of modalities: vibration and sound, vibration and temperature, temperature and sound, and each modality separately, compare in data perception and user experience of a data physicalization conveying climate change data?**

The changes in the climate can be represented by four indicators: Surface air temperature, ocean heat content, the arctic September ice area, and the land precipitation [1]. In this research three of the indicators: land precipitation, ocean temperature and air temperature will be used across 5 regions: the Indonesian sea, the North sea, the East Bering sea, the Antarctic ocean, and Greenland as the use case data. The data will be represented in a data physicalization designed for this research that allows users to select an indicator, region, and a year. The physicalization will then convey the data through temperature, vibration, and sound. This physicalization will be evaluated through a between-subject user study to evaluate the impact different (combinations of) modalities have on the accuracy, efficiency, mental load and subjective confidence.

Finally, the expected outcome of the research is a ranking of different combinations of the aforementioned modalities, based on the evaluated user experience and data perception of ordinal data in a use case of climate change.

Chapter 2 – Background Research

2.1 Data physicalization

Data physicalizations use physical representations to help people explore and interpret data, instead of the traditional data visualizations (Janssen et al. 2015). With data physicalizations, people can interact with data with more senses than only the dominant visual sense, Bae et al (2022) identify aural, tactile and taste as sensory modalities that can be used to represent data.

Using senses other than the visual sense can bring benefits to the understanding of data. Janssen et al. (2015) state that the physical form of these data representations can better exploit active perception skills, can facilitate better leverage of depth perception as opposed to traditional 2D data visualizations, and that they can make data more accessible. Furthermore, they expect more cognitive benefits, especially for physicalizations with interaction for the users. Hornecker et al. (2023) further support that physicalizations have multiple benefits over visualizations; they suggest that data physicalizations can leverage haptic memory, positively impact data perception, and allow for a better recall of the data after interacting with the physicalization. There have already been studies conducted to evaluate the effectiveness of some data physicalizations, showcasing different physical variables that can be used to encode data.

For example, Janssen et al. (2016) evaluated the use of size to represent the data. They found that 3D bar charts provided the same level of accuracy in the answers of the users as traditional 2D visualizations, using the sizes of spheres to represent data however resulted in larger error rates in the answers of participants.

Another physical modality that can be used in a data physicalization is light. Peeters et al. (2023) created a prototype of a data physicalization called “EmoClock”. EmoClock measures real-time biosignal data and from it derives the emotional state of a user, arousal or valence. The clock has an LED strip on the inner round, the color of the LED changes depending on the emotional state of users.

Yet another method to convey data through physical variables is with the use of shape changing interfaces. Daniel et al. (2019) created a shape-changing cylindrical display that conveys renewable energy availability. The system is 360°-readable, and changes its cylindrical symmetry, as the diameter of the stacked rings can change, to convey the energy availability.

In Section 2.3, two more examples of conveying data through physical variables are showcased: however with variables closely related to the research question of this paper: vibration, temperature, and sound.

2.2 Encoding data in sensory variables

Encoding variables are the properties of a material that can be used to encode data (Ranasinghe *et al,* 2023). Ranasinghe *et al,* (2023) highlight the importance of understanding encoding variables that can be perceived through various human senses. Additionally, they state that while visual variables have been well explored, the other sensory variables have not been explored as thoroughly and a common vocabulary for the other sensory variables is still missing. Hornecker *et al.* (2023) support these claims and additionally presents an attempt to establish a design vocabulary for all of the encoding variables.

The main categories of encoding variables have already been widely accepted. Both Ranasinghe *et al.* (2023) and Hornecker *et al.* (2023), mention almost the same set of sensory variable types; however, in some instances they use different terminology for the same type of variables. Hornecker et al. (2023) propose five sensory variable types: Visual, haptic, sound, taste, and smell. Ranasinghe *et al*. (2023) share these five sensory variables but add physical variables and dynamic variables for a total of seven sensory variable types. Bae *et al.* (2022) support the previous claims as visual, haptic, sonic and taste variables are identified again.

2.3 Data physicalizations using sonic and haptic variables

A few physicalizations have been developed that use sonic or haptic variables. One example is the physicalizations described in [10] by Stijn Teekens. The installation uses temperature and sound to represent global climate change data, the installation can be seen in figure 1. . The installation allows users to select a year, a CO2 level, and a country. The installation would then use sound to represent the sea level corresponding to the selection the user made. Eight speakers were used that were stacked on top of each other, the data of the sea level was encoded to the amount of speakers that would turn on. The temperature was done by using an electrical coil heater, the amount of time the heater was turned on represented the rise in temperature due to global warming. The paper mentions that using an electric coil heater to regulate temperature caused issues with the delay in warming up and cooling down. In the research, Stijn Teekens also compares whether the single modalities or the combination yields a better result. From the evaluation however, no statistical significance was found and the three conditions: Temperature, sound, Temperature and sound, were all assumed to be equal.

Figure 1. Installation of Stijn Teekens using sound and temperature [9]

Another data physicalization related directly to this research is an installation designed by van Loenhout *et al.* (2022), the installation conveys data relating to Sustainable Development Goal

(SDG) 7 (Affordable and clean energy) through vibration and temperature. The installation (as seen in figure 2.) represents either renewable energy source, or the amount of electricity generated from solar power. The data was collected from five European countries, which can be selected through country shaped buttons on a wooden map. The installation was evaluated with temperature and vibration both separately, and found that vibration was more efficient to convey real data values. For future work, van Loenhout *et al.* (2022) recommends using different data types, such as categorical data for further evaluation.

Figure 2. Data physicalization of representing SDG data through vibration and temperature [12]

2.4 Gaps in current research

The field of data physicalization is still young, and there is a general lack of empirical evaluations of the impact different modalities have on the perception of data, especially when considering combinations of modalities.

Chapter 3 - Methodology

3.1 Design and Implementation

The initial design of the installation was done on the basis of the requirements needed for the user evaluation, following the initial design the installation underwent an iterative design process during the implementation of the installation.
Before the implementation phase, the use case data was extracted and categorized into 3 categories: low, medium and high.

3.1.1 Requirements

In order to evaluate which of the combinations of sensory modalities works best, an interactive data physicalization is required that can facilitate sound, vibration and temperature. The design has the following requirements:

1. Users need to be able to select between the following 5 regions:
    - Greenland
    - The East Bering sea
    - Antarctica
    - The North Sea
    - The Indonesian Sea
2. The user should be able to select one of the 3 indicators:
    - Land precipitation
    - Ocean temperature
    - Air temperature
3. The user should be able to select a year between 1960 and 2090.
4. The installation should facilitate all 3 modalities, and provide the possibility for the researchers to turn them on and off to evaluate different combinations.
5. The installation should be intuitive to understand for users.
6. There should be no visual representation of the selected data.
7. There should be a noticeable difference between the 3 data categories.
8. The sensory modalities should not have a significant delay in representing the data after a user selects a new indicator, year or region.

3.2 Data

3.2.1 Data collection

As mentioned in chapter 1, the use case data that will be used for the installation will be data about three indicators of climate change: air temperature, sea temperature and land precipitation. 5 regions across the world will be used, these regions were selected due to both having large differences between them, and that they are spread out across the world: Greenland, the North sea, Antarctica, the Indonesian Sea and the East Bering sea. The data is based on historical emission data up to 2014, and on a Coupled Model Intercomparison Project Phase 6 (CMIP6) projection model from 2015 up to 2090 [8].

The data was extracted from the NOAA Physical Sciences Laboratory [8] for each region using 3 different Shared Socioeconomic pathways (SSPs), which are different climate scenarios of projected socio-economic changes up to 2100. Each SSP describes different climate change policies and socio-economic developments that could have an impact on the changing climate . In total there are 5 SSP models, ranging from a best case scenario to a worst case scenario [13].

To extract the data, besides choosing 3 SSP models, it is also needed to select a CMIP6 model, the desired period of the data, the season from which the data should be collected, the region, and a running mean. In table 1, the settings chosen for the datasets used in the data physicalization can be seen.

Experiment	SSP5-8.5, SSP1-2.6, SSP3-7.0
Model	Average of all models
Climatology period	1960-2090
Season	Entire year
Time average (Running mean)	10 years
Plot Area	East Bering, Greenland, Antarctica, North sea, Indonesian sea

Table 1. Settings for the extraction of data

The dataset was reduced in size by only using the first year of each decade, and by instead of using all 3 SSP models, the maximum value across the models was used. From the reduced dataset, the 3 graphs seen in figure 3 were made, the full raw data values can be seen in appendix A. As seen in the 3 graphs, the values for each region have large differences in their values.

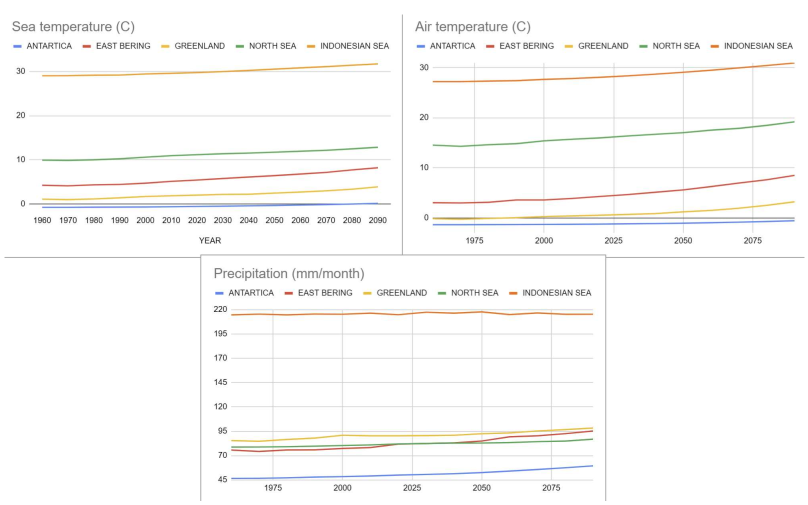

Figure 3. Air temperature, sea temperature and precipitation across the 5 regions

3.2.2 Data categorization

The design of the installation requires all 15 datasets to be categorized in 3 categories:Low, medium and high. To cluster the data in the three categories, the Jenks optimization method was used to reduce variance within groups, and maximize the variance between groups.
To use the Jenks natural optimization method, the code in Appendix H. Was used to automate the process. Before feeding the data to the Python program, the 15 datasets - one for each combination of an indicator and region - were combined in 3 datasets - one for each indicator - for the categorization.

In table 2, the data ranges for each of the 3 categories for each indicator is shown, as given by the code in appendix B. With the ranges in the table, the values for each region was mapped to one of the 3 categories, the resulting tables can be seen in appendix C.

Category	**Air temperature (c)**	**Sea temperature (c)**	**Precipitation (mm/month)**
Low (1)	-1.4 - 8.5	-0.8 - 5.4	46.6 - 59.6
Medium (2)	8.6 - 20	5.5 - 12.9	59.7- 98.4
High (3)	20.1 - 31	13 - 31.8	98.5-217.8

Table 2. The ranges for the 3 categories, resulting from the Jenks optimization method

3.3 Evaluation of modalities

To evaluate how the modalities, or combination of modalities, is best for the user experience and data perception a user study will be conducted. The user study will involve participants using the installation to answer questions about climate change.

Chapter 4 - A Data Physicalization for Representing Data using Haptic and Auditory modalities

4.1 System

The final setup of the data physicalization fulfills the previously mentioned requirements. It consists of 5 different parts that each have their own functionality: The indicator selection, the temperature modality, the vibration modality, the sound modality, and the Python program. The 5 separate parts all communicate through the Python program that runs on a laptop. The full system architecture can be seen in figure 4. The code for each of the three Arduinos can be found in Appendix C.

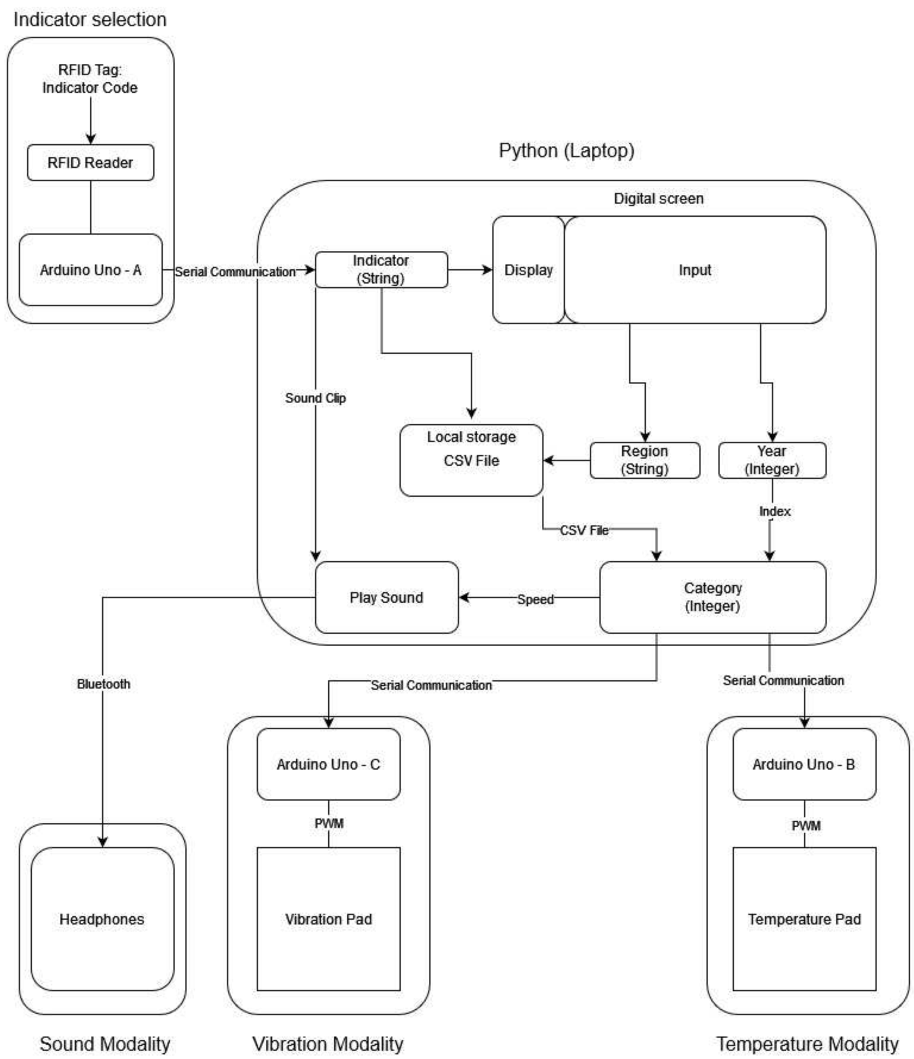

Figure 4. System architecture of the data physicalization

4.1.1 Indicator selection

The indicator selection, as seen in figure 4, consists of 3 components: Arduino Uno - A, a MFRC522 Radio Frequency Identification (RFID) reader, and 4 RFID tags. The RFID reader is connected to the Arduino Uno as seen in figure 5. When one of the 4 RFID tags is placed on top of the RFID reader, the Arduino Uno receives a code which is converted to a string corresponding to one of the indicators, or an empty string that turns off the installation.

The 3 RFID tags corresponding to the indicators all have a unique 3D model on top of them, so that users can easily identify which tag belongs to which indicator, as seen in figure 9.

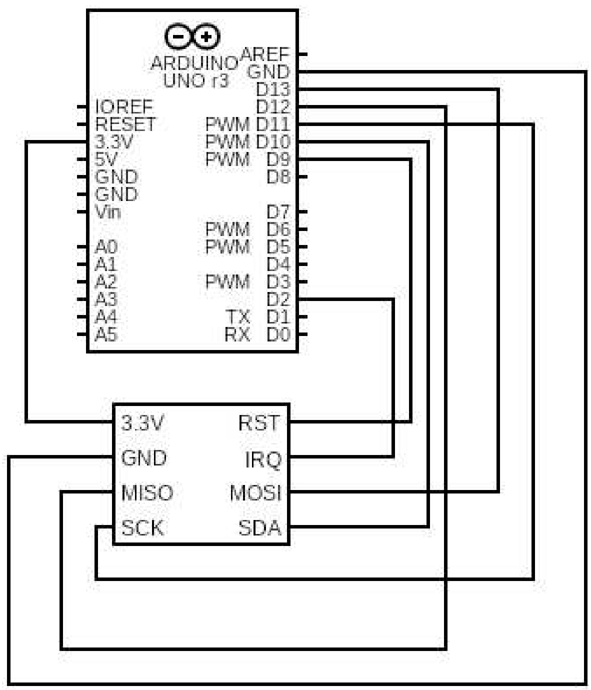

Figure 5. Circuit diagram of Arduino Uno - A

4.1.2 Temperature modality

The second part of the data physicalization is the Temperature Modality, which is powered by Arduino Uno - B. This part is responsible for the actualization of the temperature. The Arduino receives a category value (0, 1, 2, or 3) from the Python program, and will then actualise to the corresponding temperature. The circuit diagrams of the Arduino can be seen in figure 6 and figure 7.

The temperature modality makes use of a heat sink where the heating element is placed upon, this is to dissipate heat faster which decreases the time to reach the correct temperature to only 6 seconds. The heating element is covered by a 20x20 cm canvas with a hand drawn on it (labeled as B in figure 9), so users instinctively know where to place their hands: as well as to hide the electrical components and wires.

The temperature modality has the most components out of the 3 Arduinos: Arduino Uno

- B, 1 Module Peltier element, a 4 Channel relay, a heat sink, thermal glue, a fan, a power supply with 12 Volts, 2 100k Ohm resistors, and 2 10k Ohm resistors.

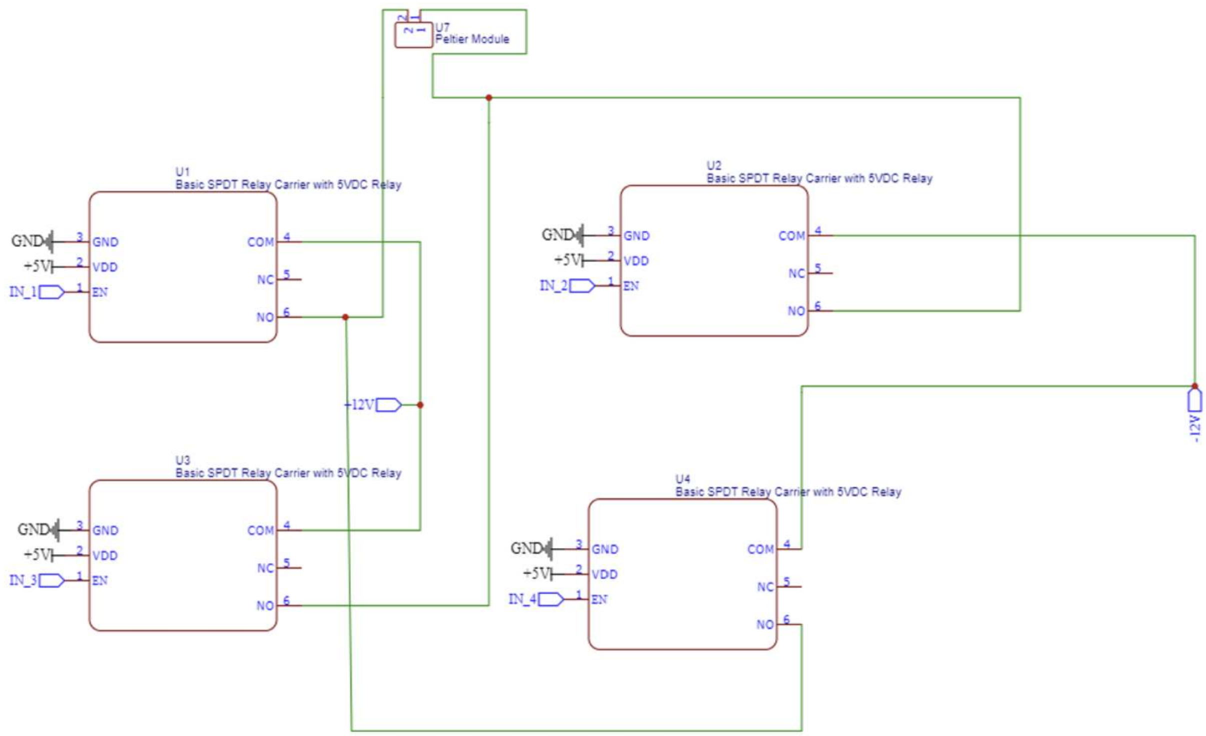

Figure 6. H Bridge diagram for the Peltier module

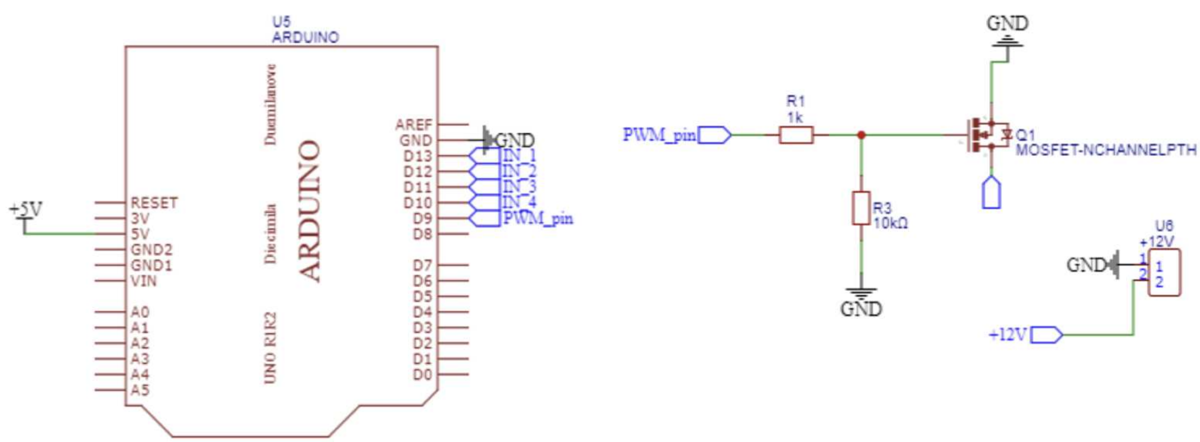

Figure 7. Circuit diagram of the temperature Arduino connection with the mosfet and power supply

4.1.3 Vibration modality

The vibration modality part is responsible for actualising the vibration based on the current category. The modality consists of 3 7500 Rotations Per Minute (RPM) KPD7C-0716 coreless vibration motors, 3 NPN mosfets, Arduino Uno - C, and a 20x20 canvas (labeled as A in figure 10). The components are connected as seen in figure 8.

Just like the temperature modality, Arduino Uno - C receives a category value from the Python program, which is then used to set the vibration motors to the correct intensity.

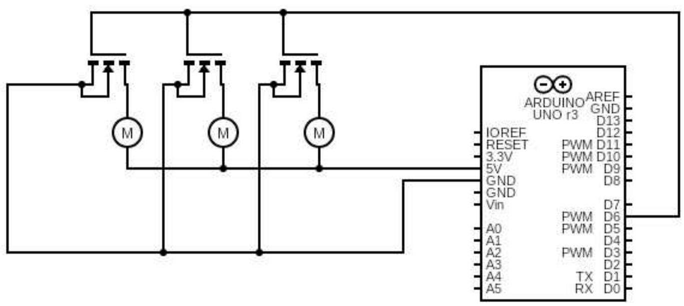

Figure 8. Circuit diagram of Arduino - C

4.1.4 Sound modality

To evaluate the auditory modality, specifically the tempo of sound, 3 different sounds are used in the installation, as each indicator has a unique sound that reflects the selected indicator:

- Rain drops for land precipitation
- Ocean waves for the sea temperature
- Wind chimes for air temperature

The different sound clips were chosen to give users an indication of what indicator is selected, otherwise this would only be known by users that read it off the display screen. As said in the previous section, there are 9 sound clips in total, as each indicator sound clip is stored in 3 different tempos. The sound is played through Bluetooth headphones connected to the laptop running the Python program.

4.1.5 Python Program

The aforementioned parts: the indicator selection, the temperature modality, the vibration modality, and the sound modality, all come together in the Python program running on the laptop. Additionally, the program included a digital input screen for the selection of the region and year, as seen in figure 9. The region and year were implemented in a digital screen, since it caused the least delays for the data physicalization.

When a region, indicator, and year have been selected the Python program uses the region and indicator to open the correct CSV file, consequently it uses the selected year as the index number to find the corresponding category value in the file. This category is only sent to the three modality parts, if the new value is different from the current value to save time by avoiding unnecessary operations. For the temperature and vibration modalities, the category value is sent over serial communication. For sound, the selected indicator and the category value are used to find the correct sound clip at the correct playback speed. The full code for the Python implementation can be seen in Appendix D.

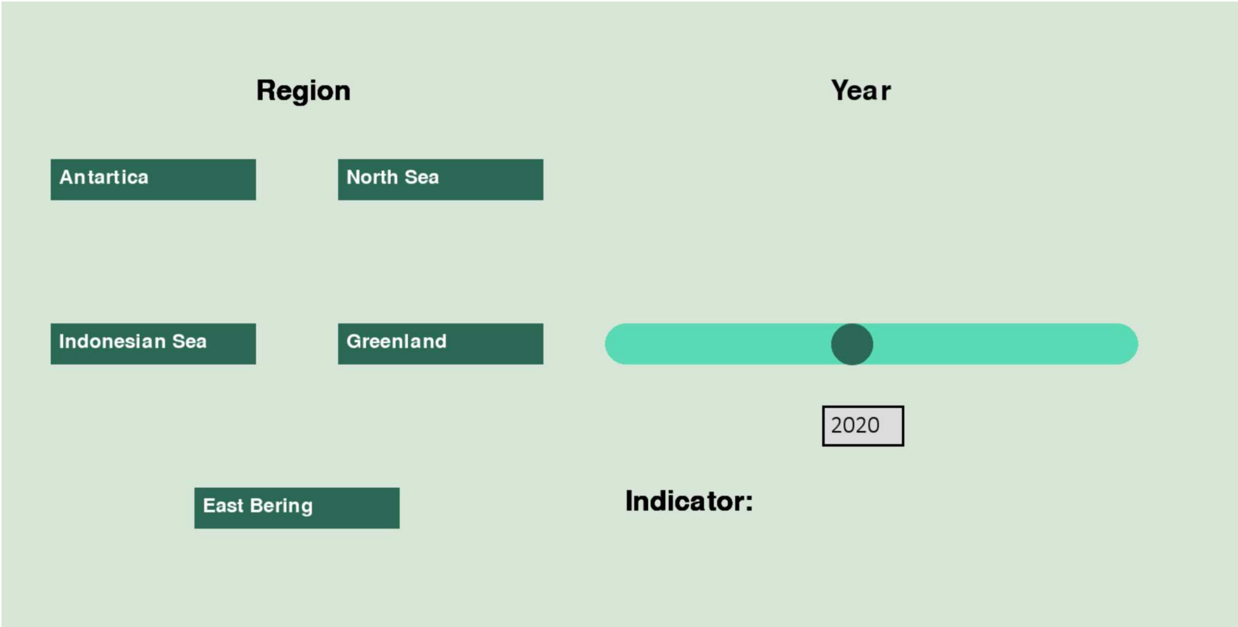

Figure 9. Digital display screen

4.2 Mapping the data to encoding variables

The three encoding variables: Temperature, vibration and sound all had to be encoded to the three categories of the data.

Vibration was encoded by using the full range of the vibration motors. The vibrations motors each have a maximum output of 7500 RPM. This maximum output was used for the High category. Both the medium and the low category were encoded by dividing the rest of the range, and testing whether the haptic feeling was distinct enough. The variable is encoded through the Pulse Width Modulation (PWM) value, where the maximum value is 150 as a higher value would destroy the motors. The values for vibration can be seen in table 3.

Category	PWM	Vibration (RPM)
Low (1)	50	2500
Medium (2)	100	5000
High (3)	150	7500

Table 3. Encoding of the vibration

Temperature was encoded through the PWM values as well, the full maximum output of the actuator was not used as it was too uncomfortable to touch for too long as it got either too hot or too cold. The values for temperature can be seen in table 4. The full range of the sensor was not used, as these temperatures were found to be too hot and cold and caused discomfort if touched for too long.

Category	PWM	Temperature(C)
Low (1)	240 (Reversed polarity)	-28.25
Medium (2)	120	33
High (3)	240	65.9

Table 4. Encoding of the temperature

Sound was encoded both through the indicator and the category, as the indicator determines which sound is played as mentioned in section 4.1.4. The category was encoded through the tempo of sound measured in Beats Per Minute (BPM). For the low category the normal speed of the sound clips was used: 120 BPM, and for the medium category this was multiplied by 2, and for the high category by 3.

Category	Tempo of the sound (BPM)
Low (1)	120
Medium (2)	240
High (3)	360

Table 5. Encoding of the tempo of sound

4.3 Full setup

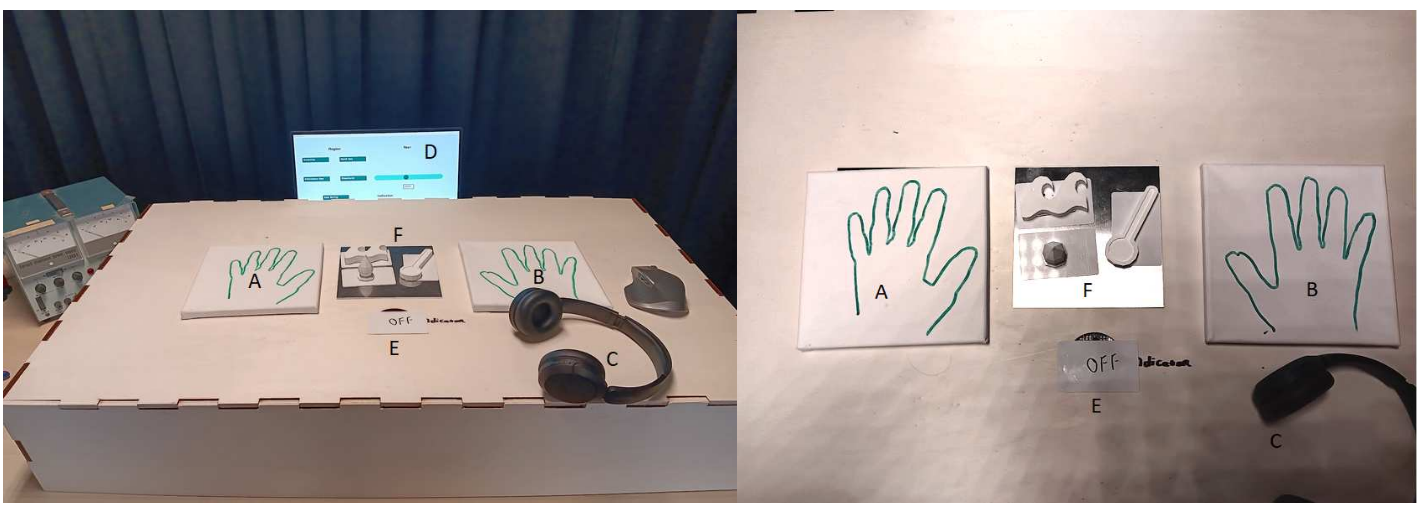

Figure 10. Final setup of the installation (A = Vibration pad, B = Temperature pad, C = Headphones, D = Digital screen, E = RFID reader, F = RFID tags).

The final setup of the installation integrates all of the parts described in section 4.1. As seen in figure 10, the installation features a large laser cut wooden box that serves as the base of the installation. Users can use the mouse to select a region and year on the digital input screen, labeled as D in figure 10 and shown in figure 9. Consequently, they can take one of the indicator RFID tags (E in figure 10) and place it upon the RFID reader labeled as F to select an indicator, which is then displayed on the screen.

When all three input variables have been selected, the vibration pad labeled as A, the temperature pad labeled as B, and the bluetooth headphones labeled as C, all actuate to the correct value that corresponds to a category low, medium, or high. The process of the user interactions can also be seen in the use case diagram in figure 11.

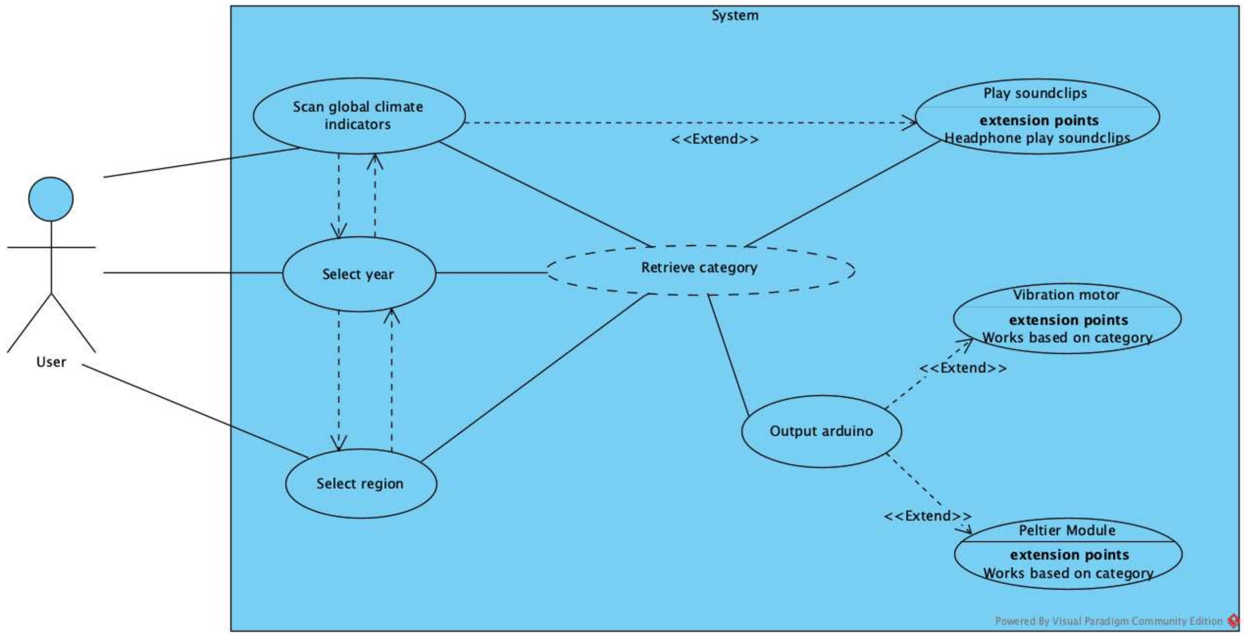

Figure 11. Use case diagram for the system

Chapter 5 - Evaluation

5.1 Experimental design

5.1.1 Goal of experiment

This chapter outlines the experimental design of the user evaluation. It includes the description of variables, the study design, the participants, the procedure, tasks, and apparatus. The goal of the experiment is to evaluate which of the different modalities, or combinations of the modalities works best conveying climate change data, and to provide a ranking of the different modalities based on efficiency, accuracy, mental load, and subjective confidence.

5.1.2 Study design

Since the goal of the experiment is to evaluate the different modalities and their combinations, the experiment will follow a between-subject design. Each participant will be assigned a single modality, or a single combination of two modalities. The reason for the between-subject design is that it minimizes the learning effect among the participants.

5.1.3 Variables

Independent variables

As the study follows a between-subject design, there is only a single independent variable. This variable is the assigned modality or the assigned combination of modalities. This ensures that the results gathered from the evaluation reflect the effect the specific modality or modalities have on the different dependent variables. In total there are six conditions for the independent variable:

1. Vibration and Temperature
2. Vibration and Sound
3. Sound and Temperature
4. Temperature
5. Vibration
6. Sound

Dependent variables

The dependent variables are the variables which were measured in the evaluation. Because participants only experience a single condition of the independent variable, the effect the modalities have on the dependent variables can be analyzed easily. In table 6, the 6 different dependent variables are listed together with how they are measured in the context of this evaluation.

Dependent Variable	**Measuring technique**
Accuracy	The number of correct answers participants submit in the questionnaire

Efficiency	The time to answer each question in the questionnaire
Mental Load	A Nasa TLX adapted to a scale from 1-10. Users answer how much mental demand was required to answer the questions.
Subjective Confidence	After each question, users state how confident they are in their answer on a scale from 1-5.
Subjective Preference	Asking users in a combination condition which of the modalities was dominant.
Subjective Feedback	Reading additional comments left by participants.

Table 6. Dependent variables and their measuring techniques

Controlled variables
To make sure all participants will have the same experience in the experiment, each participant will be provided with the same explanation on how to use the installation. Furthermore, the dataset, questions and environment will all be constant throughout all of the sessions. Controlling these variables ensures that besides the independent variable, nothing else is affecting the dependent variables so that it can be stated with certainty any potential findings are due to the modalities.

Subject variables
The only variables collected from the subjects are their age and their pre-existing climate change knowledge. This pre-existing knowledge is measured through a form with 4 multiple choice questions about climate change (Appendix G). This knowledge is measured so the results can be tested for a correlation with the pre-existing knowledge participants might have.

5.1.4 Participants

The study was conducted with 24 participants through word of mouth, social media, and emails. There were no strict requirements for participants, besides being able to speak English and that they aren’t heavily visually impaired since the region and year are displayed on a digital screen. As the study was designed as a between-subject experiment, each participant was randomly assigned one of the 6 conditions and a participant number. The distribution of the participants can be seen in table 7.

Condition/Number	Sound and Temperature	Sound and vibration	Vibration and temperature	Sound	Vibration	Temperature
1	ST1	SV1	VT1	S1	V1	T1
2	ST2	SV2	VT2	S2	V2	T2
3	ST3	SV3	VT3	S3	V3	T3
4	ST4	SV4	VT4	S4	V4	T4

Table 7. Participant distribution table

5.1.5 Procedure, tasks and apparatus

For the study, two researchers and one participant are present at a time, the time for each participant was around 25 minutes. Participants would first get a small explanation how the installation works and what the goal of the experiment is and would fill in a small form about their knowledge about climate change data. After the participant filled in the consent form, the experiment started with 2 familiarization tasks to get used to interacting with the installation. When the user understood how to use the installation, the user would fill in a questionnaire with 6 questions about the dataset, and questions about how confident they feel in their answer. After the questions were completed, the user would answer two more questions: One about the mental load, and one about further feedback. Finally, users in one of the three combination conditions were asked which of the two modalities was dominant and helped them more in answering the question. The procedure can also be seen in figure 12.

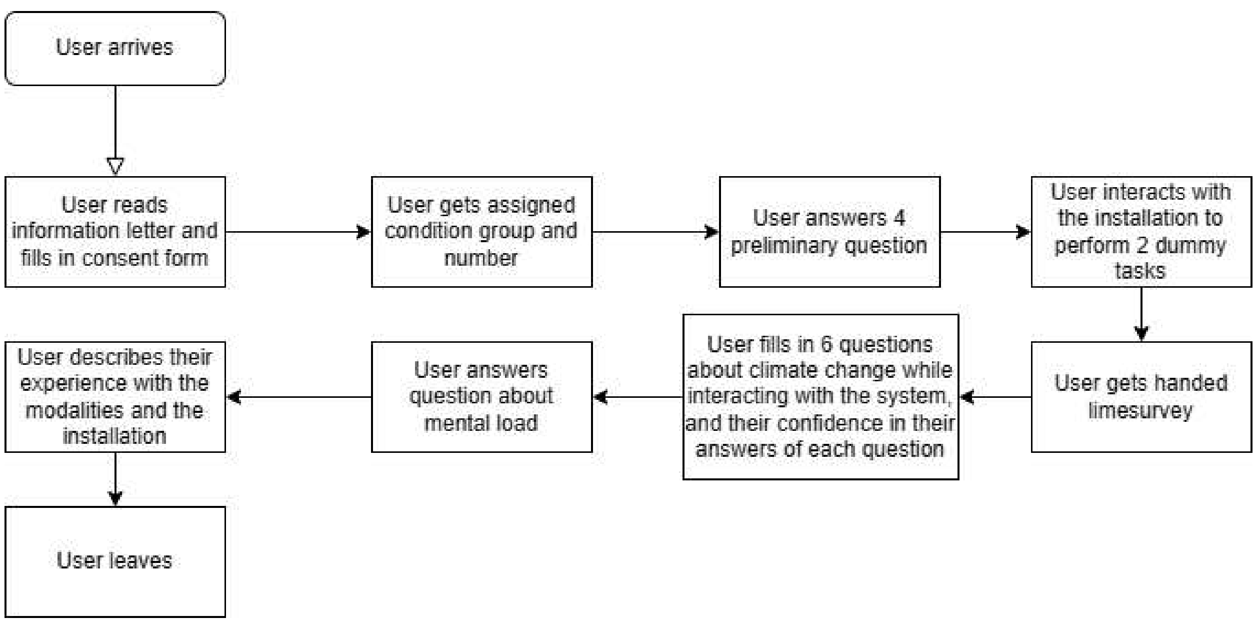

Figure 12. Procedure of the user evaluation

The tasks in the experiment can roughly be divided into four tasks, as seen in figure 13. The first task happens before the experiment. Users read the information letter (appendix E) and fill in the consent form (appendix F).

If the user gives consent, the first task starts: explanation. The explanation tasks start with the preliminary knowledge questionnaire, and following the form participants would receive a short explanation on how to use the system and perform 2 dummy tasks.

The second task is the exploration task. This phase of the experiment involves interacting with the data physicalization to answer 6 questions about climate change. After each question, participants state how confident they feel in their answer.

The final task is the evaluation task. Users answer the question about the mental load, write down any additional comments and if the user was in a combination condition, they answer the question about subjective preference.

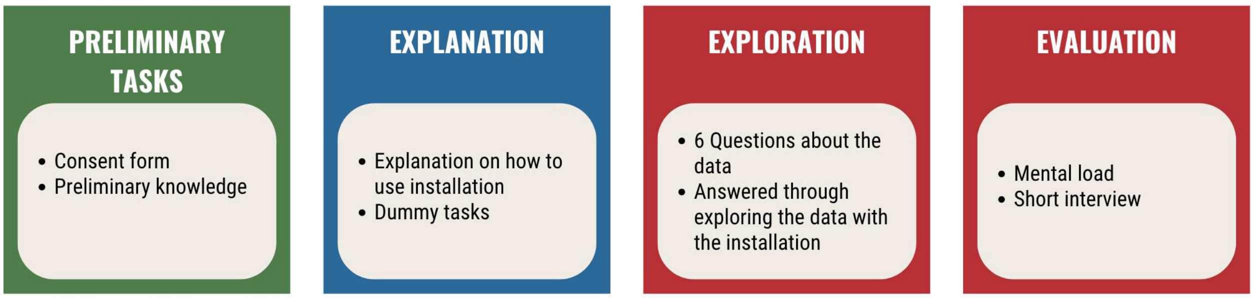

Figure 13. The four tasks of the user evaluation

Apparatus

Participants stand in front of the physicalization and interact with the different input options: indicator type, year, and region. Additionally, they experience the specific combination of modalities assigned to their group. Through Limesurvey, the researchers measure the time participants take to answer questions. Afterwards, the error rate of the answers is calculated. NASA TLX is used to evaluate the mental load, and subjective confidence is measured by asking users how confident they are in their answers on a scale from 1-10 after each question.

5.1.7 Questions

As mentioned before, each participant answered 6 questions about climate change by interacting with the data physicalization. The questions could be divided into three types of questions: ranking, comparing and identifying. In addition to the questions asked about the climate change data, users were also asked how confident they felt in their answer and how much mental demand was required. The following six questions were asked about the climate change data:

Rank question 1: *Rank the Indonesian sea, East Bering sea, and Greenland in order from low to high based on sea temperature in the year 2090.*

Rank question 2: *In the year 2050, rank the Indonesian sea, the North sea, and Antarctica in order from high to low based on precipitation.*

Identify question 1: *In the year 2030, what is the air temperature range for the North sea?*

Identify question 2: *In 2080, in what range will the sea temperature of Greenland be?*

Compare question 1: *Which one of the regions, Antarctica or Greenland, will have a higher precipitation in 2060?*

Compare question 2: *Which of the following regions (North Sea and East Bering) has the higher air temperature in 2050?*

5.2 Results

In total, 24 users participated in the study, with 4 participants in each condition. No obvious outliers were discovered in the analysis of the data, so each participant is included in the results. All of the numerical variables: Efficiency, accuracy, mental load, and confidence were analyzed in SPSS. Each variable will first be discussed between all of the conditions, and then an overall view of the three combination conditions and the three single modality conditions will be discussed.

5.2.1 Efficiency

As mentioned before, efficiency is defined as the time to answer each question, and limesurvey automatically measures the time each participant spent on each question. From there, an average time per question was calculated for each user. Between all conditions, participants spend an average of 68.6 seconds on each question. The resulting bar graphs of the result can be seen in figure 14. Overall, the combined temperature and sound have the best efficiency: with an average time to answer of 47.5 seconds, while the combined temperature and vibration have the worst efficiency at 92 seconds.

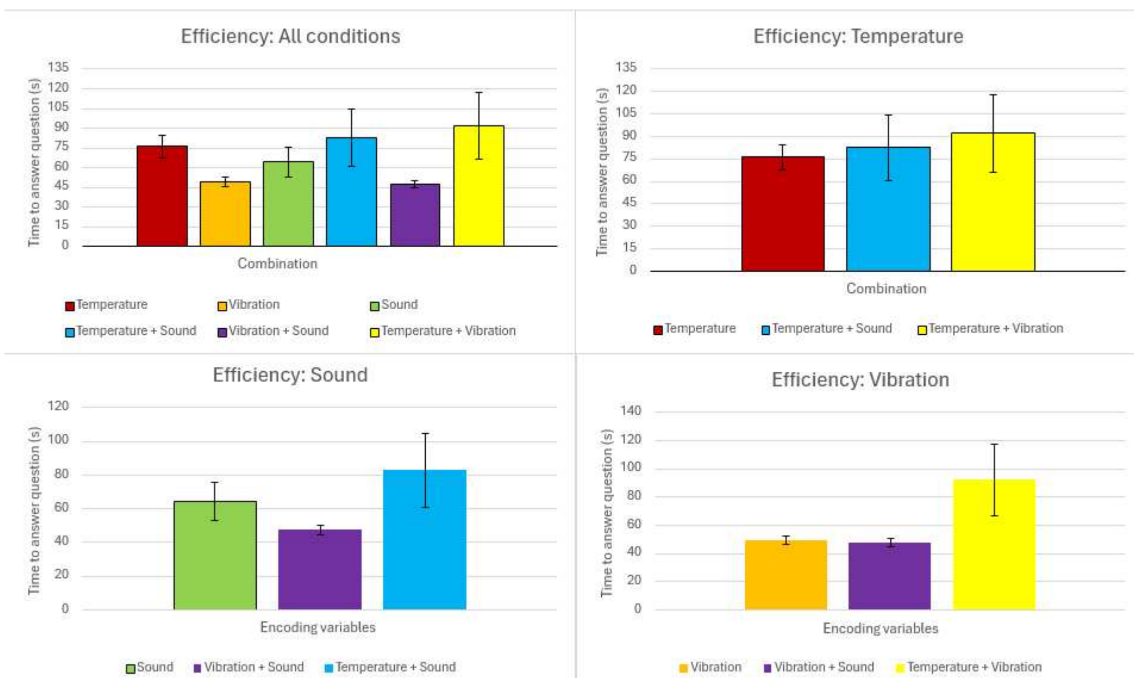

Figure 14. Mean efficiency of all conditions

To analyze the data, first the conditions were tested on normality to see if a one-way anova could be applied for the significance. As seen in figure 15. The assumption of normality holds for all conditions, except for vibration as $P_v = 0.037 < 0.05$, for this reason the null hypothesis of a normally distributed population needs to be rejected, and since the sample size is only 24, it is too small to continue with a one way anova despite the rejection of normality. So, instead of a one way anova, a non parametric Kruskal-Wallis H test is conducted.

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
T	,180	4	.	,977	4	,886
V	,302	4	.	,748	4	,037
VT	,364	4	.	,797	4	,096
S	,250	4	.	,887	4	,369
SV	,312	4	.	,894	4	,401
ST	,281	4	.	,848	4	,219

a. Lilliefors Significance Correction

Figure 15. Shapiro-Wilk test on normality for the efficiency of all conditions

For the efficiency between all of the conditions, the H0 hypothesis was an equal distribution of efficiency across the conditions, with a 95% confidence interval. As seen in figure 16, the p value of the test is 0.087. Since $P = 0.087 > 0.05$, H0 can not be rejected and the assumption of equal means between the conditions remains.

Test Statistics[a,b]

	Efficiency
Kruskal-Wallis H	9,610
df	5
Asymp. Sig.	,087

a. Kruskal Wallis Test

b. Grouping Variable: VAR00001

Figure 16. Kruskal-Wallis H test results for efficiency

However, besides the analysis of efficiency between all of the conditions it could still mean there are differences between the single modalities, and the combination conditions overall. As seen in figure 17, the single modalities seem to have a better efficiency.

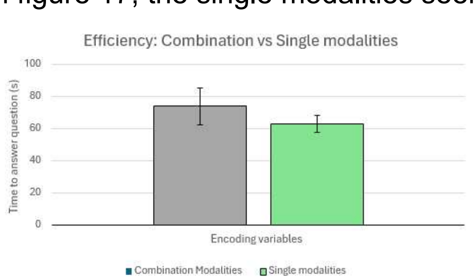

Figure 17. The efficiency of the combination conditions against the single modality conditions

Again, a test of normality was conducted to see if a T-test could be conducted. As seen in figure 17. The population is again not normally distributed, as $P_{combinations} = 0.002 < 0.05$, for this reason a T test can not be conducted. Instead, a Mann-Whitney U test was applied.

Tests of Normality

	Combination	Kolmogorov-Smirnov[a] Statistic	df	Sig.	Shapiro-Wilk Statistic	df	Sig.
Efficiency	No	,253	12	,032	,886	12	,103
	Yes	,283	12	,009	,734	12	,002

a. Lilliefors Significance Correction

Figure 18. Shapiro-Wilk test of normality between combinations and single modalities for the efficiency

Just like with the analysis between all conditions, the null hypothesis is once an equal distribution of efficiency between combined modalities, and single modalities, at a confidence interval of 95%. As seen in figure 18, the p value is 0.977, which is bigger than 0.05 so once again the null hypothesis needs to be retained.

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.[a,b]	Decision
1	The distribution of Efficiency is the same across categories of Combination.	Independent-Samples Mann-Whitney U Test	,977[c]	Retain the null hypothesis.

a. The significance level is ,050.

b. Asymptotic significance is displayed.

c. Exact significance is displayed for this test.

Figure 19. Mann-Whitney U test results for the efficiency

5.2.2 Accuracy

The accuracy, defined as the total number of correct answers, is a good reflection on how well the modalities work to convey the data. The data is represented in graphs as a sum of all correct answers within the condition group, which means the maximum possible accuracy is 24. Temperature, as well as the combination temperature and sound, both hold the highest accuracy out of the conditions: 23 correct answers out of the 24. While sound alone has the lowest accuracy with 20 out of 24. The resulting graphs can be seen in figure 20.

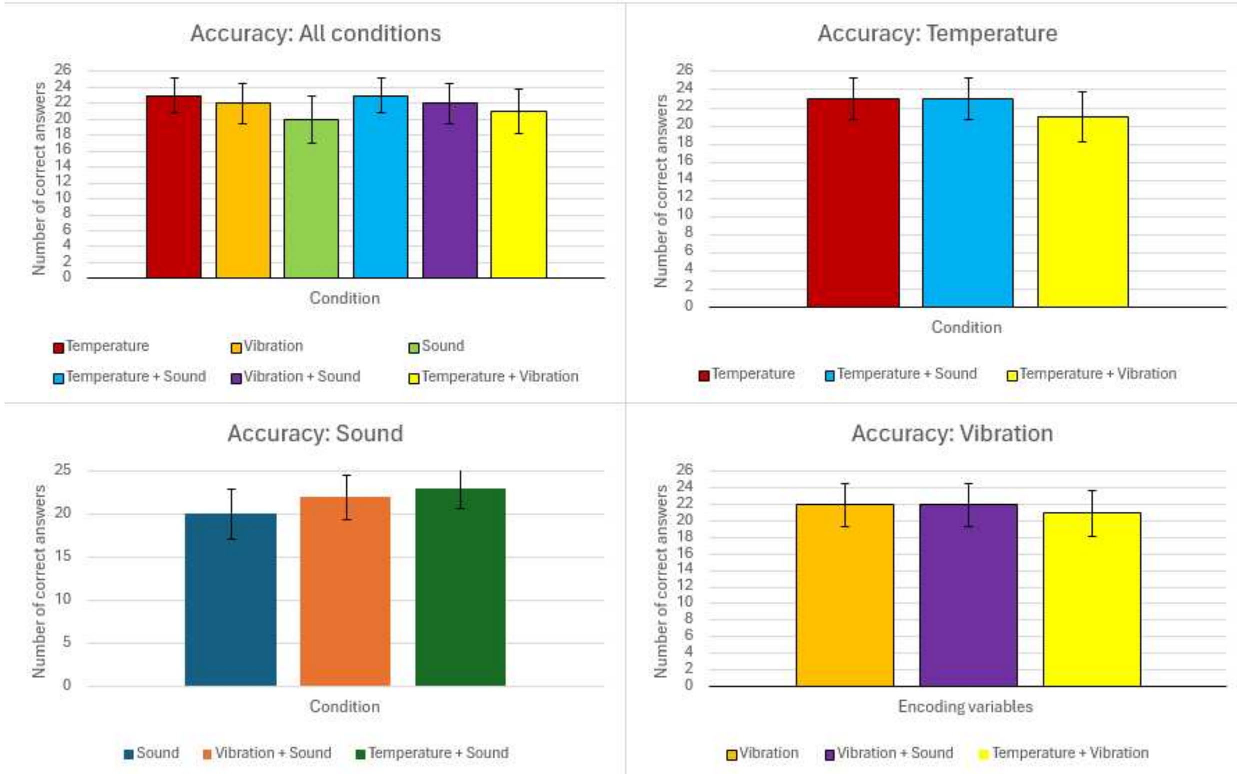

Figure 20. The accuracy of all conditions

Just like with efficiency, further tests are needed to ensure there is a significant difference between the accuracy of the conditions. As seen in figure 21, the assumption of normality does not hold up for the accuracy as 5 of the conditions have a p value smaller than 0.05, and as a result a Kruskal Wallis H test is needed to test the statistical significance.

Tests of Normality

		Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Condition	Statistic	df	Sig.	Statistic	df	Sig.
Accuracy	S	,250	4	.	,945	4	,683
	ST	,441	4	.	,630	4	,001
	SV	,441	4	.	,630	4	,001
	T	,441	4	.	,630	4	,001
	V	,307	4	.	,729	4	,024
	VT	,283	4	.	,863	4	,272

a. Lilliefors Significance Correction

Figure 21. Shapiro-Wilk test of normality for the accuracy of all conditions

The null hypothesis H0, is the same as for the efficiency: “No statistically significant differences between the distribution of accuracy across the conditions”. The Kruskal Wallis H test, as seen in figure 22, provides a p value of 0.656, which means that at a confidence interval of 95%, H0 can not be rejected. Meaning that for accuracy, there is no significant difference between the conditions.

Test Statistics[a,b]

	Accuracy
Kruskal-Wallis H	3,286
df	5
Asymp. Sig.	,656

a. Kruskal Wallis Test

b. Grouping Variable: VAR00001

Figure 22. Kruskal Wallis H test results for the accuracy

As seen in figure 23, the accuracy of the combination modality conditions seems slightly higher than the single modality conditions. However, this difference is extremely small: 66 correct answers for the combined modalities, and 65 correct answers for the single modalities. Still, the significance was tested for the combined modalities against the single modalities.

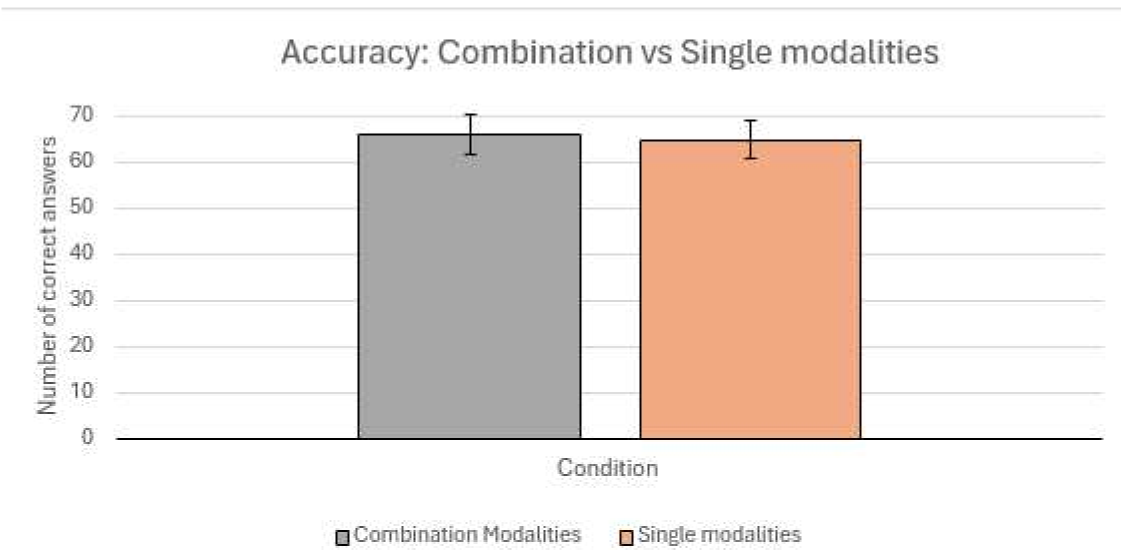

Figure 23. The accuracy of the combination conditions against the single modality conditions

The Shapiro-Wilk test on normality was performed for the accuracy between combined and single modalities, with both of the resulting p values being smaller than 0.05, as seen in figure 24, a normal distribution can be rejected completely. With normality rejected, the significance will be tested with the Mann-Whitney U test.

Through the test, the null hypothesis: “The distribution of accuracy is the same across single modalities and combined modalities” is found to be retained. As seen in figure 25, the p value is determined to be 0.671, which is larger than 0.05 and as a result, it can be stated there is no significant difference between single modalities and combined modalities in regards to accuracy.

Tests of Normality

	Combination	Kolmogorov-Smirnov[a] Statistic	df	Sig.	Shapiro-Wilk Statistic	df	Sig.
Accuracy	No	,309	12	,002	,768	12	,004
	Yes	,401	12	<,001	,662	12	<,001

a. Lilliefors Significance Correction

Figure 24. Shapiro-Wilk test of normality between combinations and single modalities for the accuracy

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.[a,b]	Decision
1	The distribution of Accuracy is the same across categories of Combination.	Independent-Samples Mann-Whitney U Test	,671[c]	Retain the null hypothesis.

a. The significance level is ,050.

b. Asymptotic significance is displayed.

c. Exact significance is displayed for this test.

Figure 25. Mann-Whitney U test results for the accuracy

5.2.3 Mental Load

The mental load was measured by asking participants how much mental demand was required to answer the questions, on a scale of 1 to 10 with 1 being the lowest and 10 being the highest. Overall, the average required mental load is 5.6, just above the middle. As shown in figure 26, all of the single modalities had the lowest mental load, 5. While temperature + vibration was measured to have the highest mental load at 6.75. Just like for accuracy and efficiency, the mental load will need to be tested for both normality and for statistical significance.

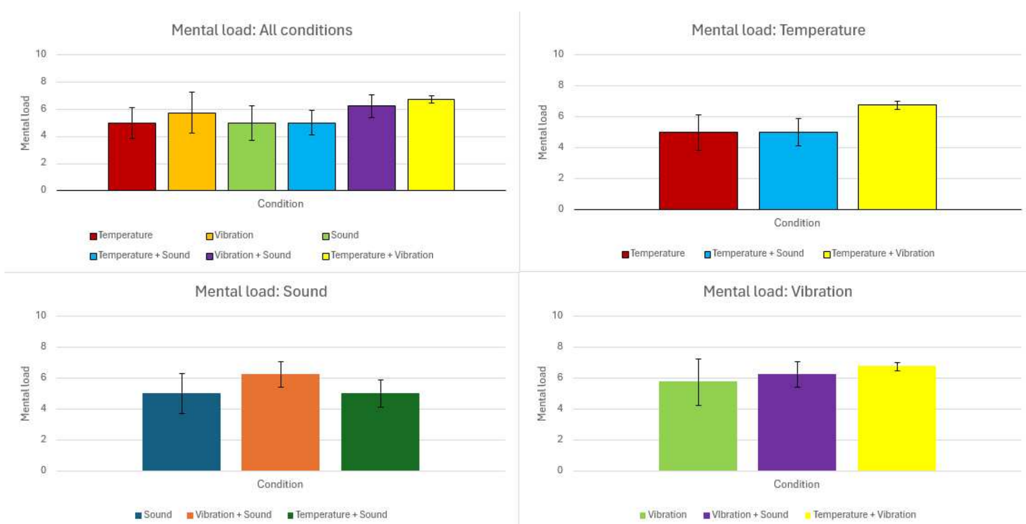

Figure 26. Mean mental load of all conditions

The assumption of normality can be rejected for the mental load. As seen in figure 27, the combination vibration and temperature, as well as only temperature both have a p value lower than the required 0.05. To test the significance of the mental load, the Kruskal-Wallis H test is again the method for the analysis.

The null hypothesis H0: “The distribution of the mental load is equal across all conditions”, was tested at a confidence interval of 95%. Once again, the null hypothesis can not be rejected as $p = 0.776 > 0.05$. For the mental load, the same holds as for efficiency and accuracy: the assumption of an equal distribution is retained due to a lack of statistical significance.

Tests of Normality

		Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Condition	Statistic	df	Sig.	Statistic	df	Sig.
Mentalload	S	,151	4	.	,993	4	,972
	ST	,208	4	.	,950	4	,714
	SV	,192	4	.	,971	4	,850
	T	,307	4	.	,729	4	,024
	V	,162	4	.	,989	4	,952
	VT	,441	4	.	,630	4	,001

a. Lilliefors Significance Correction

Figure 27. Shapiro-Wilk test of normality for the mental load of all conditions

Test Statistics[a,b]

	Mentalload
Kruskal-Wallis H	2,501
df	5
Asymp. Sig.	,776

a. Kruskal Wallis Test

b. Grouping Variable: VAR00001

Figure 28. Kruskal-Wallis H test results for the Mental Load

When comparing the mental load of the single modality conditions against the combination modalities, the combination modalities seem to have a higher mental demand than the single modalities: a mental load of 6 for the combined modalities, and 5.25 for the single modalities. The bar chart can be seen in figure 29.

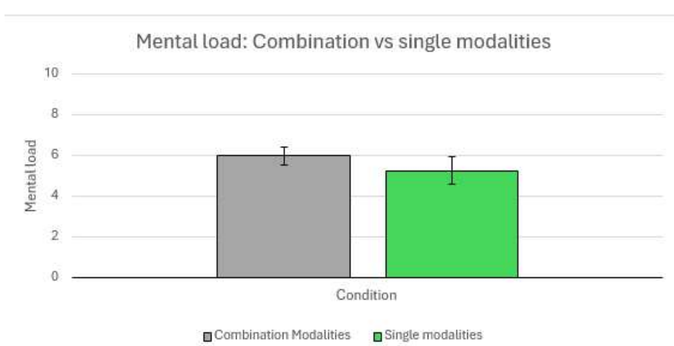

Figure 29. The mental load of the combination conditions against the single modality conditions

To make sure there is a statistical significance to this difference between the conditions, the normality was once again tested. As seen in figure 30, the Shapiro-Wilk test results in a rejection of normality, as $p_{combinations} = 0.045 < 0.05$.

With a rejection of normality, the non-parametric Mann-Whitney U test is once again used to test for significance. The null hypothesis “The distribution of mental load is the same between single modalities and combined modalities”, is not rejected by the test. The p value resulting from the test is 0.478, and since p>0.05, H0 can not be rejected.

Tests of Normality

		Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Combination	Statistic	df	Sig.	Statistic	df	Sig.
Mentalload	No	,182	12	,200*	,925	12	,329
	Yes	,250	12	,037	,857	12	,045

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

Figure 30. Shapiro-Wilk test of normality between combinations and single modalities for the mental load

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.[a,b]	Decision
1	The distribution of Mentalload is the same across categories of Combination.	Independent-Samples Mann-Whitney U Test	,478[c]	Retain the null hypothesis.

a. The significance level is ,050.

b. Asymptotic significance is displayed.

c. Exact significance is displayed for this test.

Figure 31. Mann-Whitney U test results for the mental load

5.2.4 Subjective confidence

Subjective confidence was measured by asking participants how confident they felt in their answer after each question on a scale from 1 to 5, from there the mean confidence from each participant was calculated. Overall, participants in the vibration group felt the most confident in their answer with a mean of 4.625. The participants in the temperature+vibration group felt the least confident: having a mean of 4.0. The resulting bar graph of the subjective confidence between all of the conditions can be seen in figure 32.

Before testing the significance, first it needs to be known if the data is distributed normally so a one way anova can be applied. As seen in figure 33, the assumption of normality can be rejected because $p_{temperature} = 0.024 < 0.05$, as a result the one way anova can not be applied, and instead the Kruskal-Wallis test was used again. As seen in figure 34, the results of the test was a p value of 0.569. Because the confidence interval is set at 95% for the null hypothesis “The distribution of subjective confidence is equal across all conditions”, the null hypothesis can not be rejected and remains.

Figure 32. Mean subjective confidence of all conditions

Tests of Normality

		Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Condition	Statistic	df	Sig.	Statistic	df	Sig.
Confidence	S	,257	4	.	,889	4	,376
	ST	,254	4	.	,945	4	,682
	SV	,262	4	.	,936	4	,631
	T	,307	4	.	,729	4	,024
	V	,285	4	.	,864	4	,275
	VT	,361	4	.	,792	4	,089

a. Lilliefors Significance Correction

Figure 33. Shapiro-Wilk test of normality for the subjective confidence of all conditions

Test Statistics[a,b]

	Confidence
Kruskal-Wallis H	3,868
df	5
Asymp. Sig.	,569

a. Kruskal Wallis Test

b. Grouping Variable: VAR00001

Figure 34. Kruskal-Wallis H test results for the subjective confidence

When comparing the conditions with combinations of modalities against the single modality conditions in regard to the subjective confidence, as seen in figure 35, the subjective confidence of the single modalities is slightly higher. However the difference is extremely small, the combination conditions have a mean confidence of 4.17, while the single modalities have a mean confidence of 4.42.

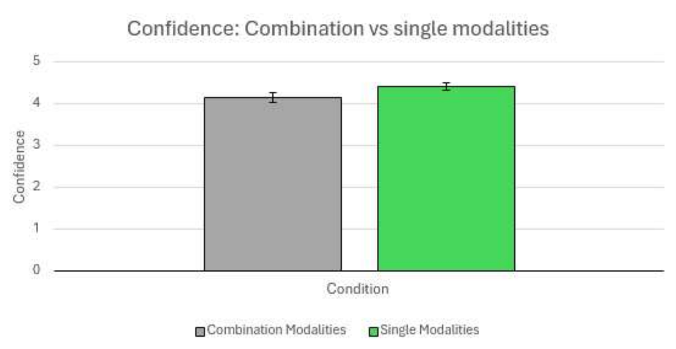

Figure 35. The subjective confidence of the combination conditions against the single modality conditions

Similar to the three other variables, the normality of the combination modalities and the single modalities was once again tested to see if a T-test could be applied for the significance. As seen in figure 36, the assumption of normality holds for the subjective confidence, which means a T-test can be applied to test the significance.

As seen in figure 37, the independent samples T-test gives a two-sided p value of 0.225, with the test being conducted with a 95% confidence interval, the null hypothesis can not be rejected since $p = 0.225 > 0.05$. This means the distribution of the subjective confidence between combination modalities and single modalities is still assumed to be equal.

Tests of Normality

		Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Combination	Statistic	df	Sig.	Statistic	df	Sig.
Confidence	No	,246	12	,044	,910	12	,215
	Yes	,106	12	,200*	,969	12	,897

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

Figure 36. Shapiro-Wilk test of normality between combinations and single modalities for the subjective confidence

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Confidence	Equal variances assumed	2,126	,159	-1,249	22	,112	,225	-,25750	,20611	-,68495	,16995
	Equal variances not assumed			-1,249	18,505	,114	,227	-,25750	,20611	-,68968	,17468

Figure 37. Independent sample T test results for the subjective confidence

5.2.5 Preliminary knowledge

As mentioned in the experimental design in chapter 5.1, the preliminary knowledge of each participant was measured by asking them 4 questions about climate change (Appendix G) that they had to answer without the installation. The measurements derived from these forms were used to test for correlations between the four qualitative dependent variables and the preliminary knowledge of participants.

As none of the data is normally distributed, as discussed in the analysis of each dependent variable, the optimal method to test for correlation is using Spearman's rank correlation coefficient. Four tests were done, one for each dependent variable. The results can be seen in figures 38-41.

Subjective confidence, mental load, and efficiency all three have a resulting p value higher than 0.05, which means there are no significant correlations between the preliminary knowledge and these three dependent variables at a 95% confidence interval. However, the correlation between accuracy and the preliminary knowledge resulted in a p value of 0.025, which is lower than 0.05. This implies that at a 95% confidence interval, there is a correlation between the accuracy and the preliminary knowledge.

The spearman correlation coefficient measures the severity of the correlation. If this value is below 0.4, it implies a weak correlation. Since the correlation coefficient of the correlation between accuracy and the preliminary knowledge is 0.457, it means that the correlation between the two is moderate.

Correlations

			PrelimKnowledge	Confidence
Spearman's rho	PrelimKnowledge	Correlation Coefficient	1,000	-,178
		Sig. (2-tailed)	.	,406
		N	24	24
	Confidence	Correlation Coefficient	-,178	1,000
		Sig. (2-tailed)	,406	.
		N	24	24

Figure 38. Spearman's rank correlation coefficient test results for the subjective confidence

Correlations

		PrelimKnowledge	Mentalload
PrelimKnowledge	Pearson Correlation	1	,381
	Sig. (2-tailed)		,066
	N	24	24
Mentalload	Pearson Correlation	,381	1
	Sig. (2-tailed)	,066	
	N	24	24

Figure 39. Spearman's rank correlation coefficient test results for the mental load

Correlations

		PrelimKnowledge	Efficiency
PrelimKnowledge	Pearson Correlation	1	-,134
	Sig. (2-tailed)		,533
	N	24	24
Efficiency	Pearson Correlation	-,134	1
	Sig. (2-tailed)	,533	
	N	24	24

Figure 40. Spearman's rank correlation coefficient test results for the efficiency

Correlations

			PrelimKnowledge	Accuracy
Spearman's rho	PrelimKnowledge	Correlation Coefficient	1,000	,457*
		Sig. (2-tailed)	.	,025
		N	24	24
	Accuracy	Correlation Coefficient	,457*	1,000
		Sig. (2-tailed)	,025	.
		N	24	24

*. Correlation is significant at the 0.05 level (2-tailed).

Figure 41. Spearman's rank correlation coefficient test results for the accuracy

5.2.6 Subjective Preference

Besides the four numerical dependent variables, participants that were part of condition groups that were given a combination of modalities were also asked which of the two modalities helped them more in finding their answers. This part will focus on the analysis of these short interview questions.

From the participants in the Vibration and Temperature condition (VT), only one participant (VT1) indicated to prefer the temperature over the vibration: *"The (vibration) noise is scary, I like the temperature sensing the most, because it has a greater indication."* They even went as far as to say the vibration felt unnecessary to find the answers to the questions. The three other participants in the group, all indicate that vibration was easier to understand and more informative than temperature. However, two participants (VT2, VT4) also described that for the vibration, it was not necessarily the haptic feedback that provided them with the information - but the sound produced by the motors.

When asked whether the combination of modalities helped the participants, and whether the modalities stimulated each other 3 of the participants indicated that they almost solely relied on a single modality: VT1 only relied on temperature and found vibration unneeded, while VT2 and VT3 relied almost exclusively on the vibration. However, VT4 stated that the information got much clearer when using both of the modalities at the same time and that even though vibration was more helpful, temperature was more engaging to experiment with.

The participants in the Sound and Temperature condition (ST) overall indicated a preference for the temperature (ST1, ST3, ST4), however ST2 indicated that the temperature feedback could be confusing as it took time to heat up or cool down - while the sound modality instantly changes, for that reason they stated that the audio was easier to understand than the temperature.

Regarding the combination of the modalities, 3 out of the 4 participants in the group enjoyed the combination. "*The sound is in indication, and the temperature justifies it.*" (ST1), as ST1 describes, the sound gives an immediate indication of what the value could be however temperature was needed to justify the answer to be confident. ST4 described that while they mostly used the temperature feedback, the audio helped them to be more immersed and engaged with the data physicalization. In contrast to the others, ST3 focused almost solely on the temperature while ignoring the auditory modality.

The final combination condition Sound and Vibration (SV) showed an overall preference to vibration (SV1, SV2, SV4), they stated that the vibrations were more straightforward and were better at indicating differences. SV3 contrasted from the others in the group, as they described they used both the audio and the vibration equally as sometimes it was easier to differentiate through the audio, and at other times through the vibrations.

Regarding the combination of modalities, the participants each enjoyed having more than a single modality, SV3 used the combination the most as described above.

Overall, participants who were either in the Sound and Temperature group, or the Vibration and Sound group preferred the haptic modality over the auditory, with only a single participant (ST2) relying more on the auditory modality, and one other participant (SV3) who did not have a preference. When looking at the Vibration and Temperature group, the participants relied more on vibration however this is mostly due to the sound the motors made.

5.2.7 Subjective Feedback

All of the participants also were asked for any further comments or feedback on the data physicalization. In this section, the comments and feedback points that occurred the most throughout the user study will be highlighted.

Throughout the user study, four participants interacting with the temperature modality (VT1, VT3, ST1, ST2) stated that the temperature modality was confusing due to the time it took to reach the correct temperature after selecting the year, region, and indicator, while the other modality they interacted with had instantaneous feedback. The four participants all suggested that there should be a timer displayed on the screen, that shows when to start feeling the modalities. The participants in the only Temperature condition, did not indicate a need for such a timer.

Additional comments were made about the temperature modality. T1 and VT3 both state that it is easy to distinguish between the low and the high categories through the temperature. However, it is difficult to distinguish between the mid and the high category through the temperature alone.

Five of the participants who interacted with the vibration modality (VT1, VT2, VT3, VT4, V3) all indicated a need for the noise of the vibration motors be reduced. VT1 and VT3 did not correlate the noise of the motors with the corresponding data, however VT1 found the noise scary, while VT3 found it distracting. The three other participants indicating the noise of the motors (VT2, VT4, V3) actually used the noise produced by the motors to find the correct answers, as the motors make more noise as their RPM increases, which correlates directly to the data values. For both the participants that found the sound uncomfortable, and those who used it to find the answer the noise should be reduced.

Besides the three previous comments about the modalities themself, participants also indicated a need for a better user experience. One of these comments had to do with the region selection. The regions were all listed on the screen as buttons, however some participants did not know where some of the regions were located geographically. V1 and ST1 suggest a visual display of the regions on either a map or a globe, so everyone can know where each region is located.

Additionally, from the comments of two participants (S3, VT4) it seems like a physical interface to select the region and year would be better than the current digital screen. S3 states that the indicator selection with the 3D models and the RFID reader was interactive and engaging, while selecting a year and region was dull and boring. VT4 states that the computer mouse needed to select something on the screen distracted them from keeping both hands available for the feeling of the modalities, and eventually used only the vibration as their right hand was constantly on the mouse.

The final comment made by multiple participants has to do with the overall aesthetic of the data physicalization. VT3 found the digital input screen confusing as the cursor was small and disappeared in the background, they suggest improving the Graphical User Interface (GUI). While ST1 states the installation could look more professional, and both the box and the 3D Models of the indicators could be painted to provide a more pleasing aesthetic.

5.3 Implications of Results

The results of the user study can be broadly divided into quantitative and qualitative results. The analysis of all quantitative variables: efficiency, accuracy, mental load, and subjective confidence, all resulted in the same conclusion, there is no statistically significant difference between any of the conditions in any of the quantitative variables. This implies that for these four variables, it does not matter which of the modalities, or combination of modalities, is used. Furthermore, there is also no statistically significant difference between experiencing a single modality, or a combination of modalities.

The qualitative analysis shows that while it might hold true that objectively the chosen modality does not matter, participants still have a personal preference. From the 12 participants who were in one of the combination groups, the haptic modalities were preferred. This could be explained by the haptic feedback being experienced as more engaging and interesting than the simple auditory modality.

When comparing between the two haptic modalities, temperature and vibration, more participants found the vibration to be easier to understand and more dominant. However, it is unclear whether this is due to the haptic feeling of the vibration, or due to the sound that the motors make. Furthermore, it could be true that the temperature would be found more useful if the problem of the sensor being delayed by the dissipation could be eliminated further.

All in all, it seems that objectively it does not matter what modality is experienced by a participant, nor does it matter if they experience a single modality or a combination. However, haptic feedback is preferred by a majority of participants over auditory feedback.

Chapter 6 - Discussion

The goal of the research was to facilitate a multimodal data physicalization to convey climate change, using vibration, temperature, and sound as the variables to convey the data. Following the implementation, the goal was to evaluate which of the modalities or combination of modalities performed the best on efficiency, accuracy, mental load, and subjective confidence. In this chapter, the limitations of the research will be described first. Consequently, recommendations on how to improve the data physicalization and the user evaluation will be outlined for future research.

6.1 Limitations

Multiple limitations were encountered in both the implementation of the data physicalization, as well as with the user evaluation itself. First, the limitations regarding the installation itself will be discussed.

Originally, the data physicalization was planned to be more advanced than the final version. In the initial plan, there was no digital display screen for the selection of the regions and year. These selections were done with a physical interface. For the year selection, the plan was to implement a year knob that users would rotate clockwise to increase the year, and counterclockwise to decrease the year. The year knob was implemented and worked, however it was difficult to interact with as it was too small, making it almost impossible to select a specific year as even the slightest movement changed the year greatly.

The regions were originally planned to be implemented in a physical globe. The globe would have buttons on the locations of the 5 regions used in the dataset, and by pressing it the corresponding region would have been selected. The globe was created, and the buttons implemented with the help of an ESP32 microcontroller to make the globe wireless. However, this came with some severe limitations: the ESP32 did not communicate instantly with the python program, occasionally it could take up to a minute for the region to be properly selected. A decision was made to switch the ESP32 for a fourth Arduino Uno, sacrificing the wireless aspect of the globe. Unfortunately, this also did not work as the cables connecting the globe with the laptop were messy and unstable. As a result, if a user picked up the globe recklessly the cable would fall out.

A decision was made to completely remove the globe and the year knob, as there was simply not enough time to implement them properly in the installation, and they were replaced with the current digital input screen.

Another limitation had to do with a possible fourth modality, Electrical Muscle Stimulation (EMS). EMS was planned to be a fourth modality in the research, as it has not been used before in a data physicalization. Unfortunately, the implementation of EMS proved difficult due to multiple factors: safety, cost, and time constraints. Since the EMS has to work automatically like the other modalities, it was attempted to create such a device. However, the components broke quickly due to a lack of knowledge and information on how to build one safely. Consequently, the plan was to use an existing EMS device and to manually control the EMS for participants. But since the three other modalities did work automatically, this would be inconsistent with the overall physicalization and as a result EMS was removed from the research plan.

The vibration motors were an additional limitation to the research. As described in chapter 5.2.7, multiple participants pointed out the noise that the vibration motors made. This noise was already discovered before the user evaluation in the implementation phase, the problem could perhaps have been solved or reduced by using different types of vibration actuators. However, there was a lack of budget and time to implement new vibration motors.

Besides the limitations in the implementation phase of the data physicalization, there were also a couple of limitations during the user evaluation.

The first and largest limitation had to do with the amount of participants. In the initial experimental design, it was decided to have 36 participants in the user study, 6 in each condition. The final outcome of the experiment only involved 24 participants, 4 in each condition. This was due to various factors.

One of these factors was simply time constraints, with more time eventually all 36 evaluations could have been conducted. However, the 36 participants could still have been conducted in the same timeframe if it was not for additional factors.

During the evaluation, there were 2 participants who eventually had to be removed from the results. This was due to them misunderstanding how the data physicalization worked. Instead of interpreting a higher output of the modalities as a higher value in the data, they assumed the opposite. For example, they correlated the high category for the temperature modality, with a lower sea temperature. As a result, these 2 participants were replaced, which takes away from the total number of participants.

Another factor was a lack of responses. Multiple messages have been sent out to multiple groups of students to ask them to participate, however the amount of responses was always low.

With only 24 participants, and small differences in the results of each condition, it does not come as a surprise that the results are statistically insignificant.

6.2 Recommendations

From the feedback gathered through the user evaluations, observations, and prior known limitations, multiple recommendations can be made to both the improvement of the data physicalization and the experimental design of the research. First, recommendations concerning the data physicalization will be discussed and then the recommendations for the experimental design.

The first recommendation has to do with the design of the data physicalization, during the design process there was no focus on a specific target group. However, one of the participants (S3) said the installation should have a specific target group, as currently it gets boring for adults fast. Keeping in mind what users will interact with the physicalization could provide new insights in how to better stimulate the engagement of users.

Another recommendation to improve the engagement and immersion of users has been described in chapter 5.2.7, the aesthetic of the installation. Both the physical aspects, such as the box and the 3D Models of the indicators, and the GUI of the input screen, could benefit from being more interesting visually and more professional.

However, instead of improving the visual aesthetic of the GUI, it could also be recommended to remove the GUI altogether and to replace it with a physical interface. As discussed both in chapter 6.1 and 5.2.7, having a physical representation for the regions such as a globe would especially have benefits. As currently, some users do not know the geographic locations of each region, which could help them to already have an initial idea about the climate in the region.

Perhaps the most important recommendations to improve the installation have to do with the vibration motors and the heating element. For the vibration motors, it is recommended to find a method to minimize the interference of the sound of the motors. For example, through the use of noise canceling headphones, or by using vibration motors that make less sound.

For temperature, something should be done about the delay. Unfortunately, it is impossible to make the temperature feedback instantaneous such as the vibration and sound. However, there are two solutions that could work. The first solution is to introduce an artificial delay to the other modalities, this way participants who have multiple modalities will not already know the answer before feeling the temperature. The second solution is to implement a timer, as suggested by some of the participants. This timer could indicate when to start feeling the feedback from the modalities.

The next recommendation has to do with the user evaluations. The recommendation regarding the user evaluation, is to include more participants in the study. As mentioned in the previous section, originally 36 participants were planned. Involving at least 36 participants would increase the reliability of the experiment, and it might even lead to a greater statistical significance. Involving even more than 36 participants could lead to even more findings. In short, it is recommended to include more participants in the user evaluation.
Besides improving the current modalities, design, and experimental design, it could be interesting for future research to expand on the current physicalization.

The most obvious recommendation is to conduct a similar study, however with more types of modalities. One example would be the use of EMS, as described in 6.1. Involving more modalities, and thus combinations, in the research could provide a larger overview of the effect different modalities have on the data perception based on efficiency and accuracy.

Besides including more modalities, the data physicalization also produces the opportunity to involve more data. Currently, three indicators can be seen across five regions. This dataset can be expanded to convey a more comprehensive view of global climate change. For example, by including more geographically diverse regions in the dataset. Besides using more regions, the different SSP models could also be included, so users can experience different scenarios for the future.

All in all, the research provides multiple opportunities for possible future research. Future research could focus on involving more modalities, more comprehensive datasets, or simply more participants.

Chapter 7 - Conclusion

The goal of this research was to find which modality, or combination of modalities performed best on the ground of efficiency, accuracy, mental load and subjective confidence. To answer the research question:
How do different combinations of modalities: vibration and sound, vibration and temperature, temperature and sound, and each modality separately, compare in data perception and user experience of a data physicalization conveying climate change data?

As a means to answer the question, a data physicalization conveying climate change data through sound, temperature, and vibration has been implemented and tested in a between-subject user study. The expected outcome of the research was a ranking of the modalities and the combination of modalities, based on the data perception and the user experience.

The results of the evaluation have been thoroughly analyzed and tested for significance, and the expected outcome can not be achieved. Through the user study, it was found that there is no statistically significant difference between the conditions based on the data perception and the user experience. In other words, all of the conditions are still assumed to be equal based on the efficiency, accuracy, mental load, and subjective confidence. Furthermore, the same holds true when comparing combinations of the modalities against the single modalities in a broad view. However, when looking at the subjective responses it could be that vibration and temperature provide a better user experience than sound, since most participants involved in combination groups prefer the haptic modalities.

Future research could attempt to repeat the research, but with a larger sample size in the user evaluation to test if the lack of significance is due to a small sample size, or due to the modalities truly being equal in data perception and user experience. Additionally, more research could be done involving more types of modalities in addition to temperature, vibration, and sound. This could provide a detailed understanding of how different modalities affect data perception and user experience.

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Appendices

Appendix A - Raw data tables

Sea temperature (c)					
YEAR	ANTARCTICA	EAST BERING	GREENLAND	NORTH SEA	INDONESIAN SEA
1960	-0.787	4.206	1.055	9.903	29
1970	-0.786	4.084	0.953	9.854	29.07
1980	-0.762	4.305	1.103	9.988	29.17
1990	-0.73	4.398	1.361	10.216	29.2
2000	-0.713	4.681	1.671	10.583	29.45
2010	-0.656	5.095	1.823	10.918	29.6
2020	-0.587	5.39	1.968	11.146	29.77
2030	-0.528	5.747	2.139	11.366	30
2040	-0.456	6.086	2.177	11.515	30.25
2050	-0.372	6.4	2.433	11.708	30.55
2060	-0.274	6.759	2.677	11.928	30.84
2070	-0.172	7.132	2.955	12.144	31.11
2080	-0.051	7.697	3.319	12.466	31.44
2090	0.108	8.18	3.858	12.834	31.73

Air Temperature (c)					
YEAR	ANTARCTICA	EAST BERING	GREENLAND	NORTH SEA	INDONESIAN SEA
1960	-1.380209	3.0219095	-0.17768703	14.526618	27.22284
1970	-1.3775455	2.9695444	-0.28414604	14.2884245	27.223225
1980	-1.3603265	3.0969477	-0.13846058	14.611463	27.328102
1990	-1.3446404	3.563328	0.023758944	14.813458	27.411566
2000	-1.3273474	3.563328	0.24802485	15.387142	27.670351
2010	-1.300492	3.867253	0.37592006	15.699911	27.842857
2020	-1.2566209	4.260484	0.51469785	15.976133	28.089302
2030	-1.2014216	4.6393156	0.67287135	16.356726	28.381868
2040	-1.1529887	5.108438	0.8404033	16.698553	28.715195
2050	-1.0837492	5.577554	1.1867079	17.018547	29.094467
2060	-0.9822768	6.2450843	1.4747189	17.520964	29.499388
2070	-0.8660182	6.9431934	1.9128381	17.881319	29.96765

2080	-0.73973155	7.602934	2.4956026	18.478422	30.442904
2090	-0.5795084	8.485696	3.199688	19.179396	30.940151

Precipitation (mm/month)					
YEAR	ANTARCTICA	EAST BERING	GREENLAND	NORTH SEA	INDONESIAN SEA
1960	46.63424	75.76081	85.529205	78.86867	214.64616
1970	46.751106	74.33614	84.77062	78.89397	215.43149
1980	47.258038	75.865456	86.63191	79.2297	214.63991
1990	48.046764	75.9971	88.06868	79.76511	215.50551
2000	48.460667	77.424644	90.97328	80.42478	215.28821
2010	49.154755	78.32	90.39898	81.03121	216.4048
2020	50.075226	81.883766	90.43819	82.093315	214.78242
2030	50.732517	82.5074	90.61539	82.54581	217.37332
2040	51.47054	83.20935	90.98518	82.95261	216.35822
2050	52.624866	85.04845	92.51462	82.9905	217.73274
2060	54.170116	89.40599	93.39386	83.46816	214.93945
2070	55.79932	90.42486	95.40317	84.45225	216.60785
2080	57.59736	92.62039	96.747536	84.994865	215.24591
2090	59.55291	95.33483	98.39734	86.942604	215.29945

Appendix B - Categorised data tables

Sea Temperature					
YEAR	ANTARCTICA	EAST BERING	GREENLAND	NORTH SEA	INDONESIAN SEA
1960	1	1	1	2	3
1970	1	1	1	2	3
1980	1	1	1	2	3
1990	1	1	1	2	3
2000	1	1	1	2	3
2010	1	1	1	2	3
2020	1	1	1	2	3
2030	1	2	1	2	3
2040	1	2	1	2	3
2050	1	2	1	2	3
2060	1	2	1	2	3
2070	1	2	1	2	3
2080	1	2	1	2	3
2090	1	2	1	2	3

Air Temperature					
YEAR	ANTARCTICA	EAST BERING	GREENLAND	NORTH SEA	INDONESIAN SEA
1960	1	1	1	2	3
1970	1	1	1	2	3
1980	1	1	1	2	3
1990	1	1	1	2	3
2000	1	1	1	2	3
2010	1	1	1	2	3
2020	1	1	1	2	3
2030	1	1	1	2	3
2040	1	1	1	2	3
2050	1	1	1	2	3
2060	1	1	1	2	3
2070	1	1	1	2	3
2080	1	1	1	2	3

2090	1	1	1	2	3

Precipitation					
YEAR	ANTARCTICA	EAST BERING	GREENLAND	NORTH SEA	INDONESIAN SEA
1960	1	2	2	2	3
1970	1	2	2	2	3
1980	1	2	2	2	3
1990	1	2	2	2	3
2000	1	2	2	2	3
2010	1	2	2	2	3
2020	1	2	2	2	3
2030	1	2	2	2	3
2040	1	2	2	2	3
2050	1	2	2	2	3
2060	1	2	2	2	3
2070	1	2	2	2	3
2080	1	2	2	2	3
2090	1	2	2	2	3

Appendix C - Arduino code

```
//Indicator Arduino
// initialize the values

#include <SPI.h>
#include <MFRC522.h>

#define RST_PIN         9          // Configurable, see typical pin layout above
#define SS_PIN          10         // Configurable, see typical pin layout above

MFRC522 mfrc522(SS_PIN, RST_PIN);   // Create MFRC522 instance
int prevValue = 0;
//int prevYear = 0;
String prevIndic = "PREC";
int category = 0;
String indic = "0";
//int year = 0;


void setup() {
  // initialize serial communication at 9600 bits per second:
  Serial.begin(115200);
  SPI.begin();                                       // Init SPI bus
  mfrc522.PCD_Init();
}

// the loop routine runs over and over again forever:
void loop() {
  // read the input of th year knob:
 // int sensorValue = analogRead(A0);

  if (mfrc522.PICC_IsNewCardPresent()) {
    String uid = String(getID());

    getIndicator(uid);
  }

  Serial.println(indic);     //Send all new input information to Python


  delay(1);

}

void getIndicator(String id) {
  if (id == "27374") {
    indic = "Prec";
  } else if (id == "25582") {
```

```
    indic = "ST";
  }
  else if (id == "30446") {
    indic = "AT";
  }
  else{
    indic = "0";
  }
}


unsigned long getID() {
  if ( ! mfrc522.PICC_ReadCardSerial()) { //Since a PICC placed get Serial and continue
    return 0;
  }
  unsigned long hex_num;
  hex_num =  mfrc522.uid.uidByte[0] << 24;
  hex_num += mfrc522.uid.uidByte[1] << 16;
  hex_num += mfrc522.uid.uidByte[2] <<  8;
  hex_num += mfrc522.uid.uidByte[3];
  mfrc522.PICC_HaltA(); // Stop reading
  return hex_num;
}
```

```
//Vibration Arduino
int input = 0;
void setup() {
  Serial.begin(9600);
}

void loop() {

  if (Serial.available() > 0) {
    char input = Serial.read();
    if (input == '1') {
      analogWrite(6, 50);  // Set PWM output based on the received value
    } else if (input == '2') {
      analogWrite(6, 100);  // Set PWM output based on the received value
    }
    else if (input == '3') {
      analogWrite(6, 150);  // Set PWM output based on the received value
    }
    else if (input == '0'){
      analogWrite(6, 5);
```

```
    }
  }
}
```

```
//Temperature Arduino
//LOOK AT THE SCHEMATIC
//#include <esp_now.h> // esp module

int RELAY_PIN_Positive_1 = 13;
int RELAY_PIN_Negative_1 = 12;
int RELAY_PIN_Positive_2 = 11;
int RELAY_PIN_Negative_2 = 10;

const int pwmPin = 9;  // PWM pin to control the MOSFET
int pwmValue = 0;      // Variable to store PWM value (0-255)
int input = 0;
void setup() {
  Serial.begin(9600);
  pinMode(RELAY_PIN_Positive_1, OUTPUT);
  pinMode(RELAY_PIN_Negative_1, OUTPUT);
  pinMode(RELAY_PIN_Positive_2, OUTPUT);
  pinMode(RELAY_PIN_Negative_2, OUTPUT);
  pinMode(pwmPin, OUTPUT);  // Set PWM pin as an output
}

void loop() {

  if (Serial.available() > 0) {
    char input = Serial.read();
    if (input == '1') {
      //Serial.println("Input 1");
      digitalWrite(RELAY_PIN_Positive_1, LOW);
      digitalWrite(RELAY_PIN_Negative_1, HIGH);
      digitalWrite(RELAY_PIN_Positive_2, LOW);
      digitalWrite(RELAY_PIN_Negative_2, HIGH);
      analogWrite(pwmPin, 240);  // Set PWM output based on the received value
      //Serial.print("PWM Value set to: ");
      // Serial.println(100);
    } else if (input == '2') {
      //Serial.println("Input 2");
      digitalWrite(RELAY_PIN_Positive_2, HIGH);
      digitalWrite(RELAY_PIN_Negative_2, LOW);
      digitalWrite(RELAY_PIN_Positive_1, HIGH);
      digitalWrite(RELAY_PIN_Negative_1, LOW);
```

```
      analogWrite(pwmPin, 100);  // Set PWM output based on the received value
      //Serial.print("PWM Value set to: ");
      //Serial.println(40);
    }
    else if (input == '3') {
      //Serial.println("Input 3");
      digitalWrite(RELAY_PIN_Positive_2, HIGH);
      digitalWrite(RELAY_PIN_Negative_2, LOW);
      digitalWrite(RELAY_PIN_Positive_1, HIGH);
      digitalWrite(RELAY_PIN_Negative_1, LOW);
      analogWrite(pwmPin, 240);  // Set PWM output based on the received value
      // Serial.print("PWM Value set to: ");
      //Serial.println(155);

    }
    else if (input == '0') {
      digitalWrite(RELAY_PIN_Positive_2, HIGH);
      digitalWrite(RELAY_PIN_Negative_2, LOW);
      digitalWrite(RELAY_PIN_Positive_1, HIGH);
      digitalWrite(RELAY_PIN_Negative_1, LOW);
      analogWrite(pwmPin, 0);  // Set PWM output based on the received value
    }
  }
}
```

Appendix D - Python code

```
import serial
import time
import pandas as pd
import winsound
import pygame
import pygame_widgets.slider as pgw
import pygame_widgets
from pygame_widgets.textbox import TextBox

# Variables
prev_Indic = "0"
prev_Region = "0"
prev_Year = 0
category = 0
value = 0

# Serial ports
ser1 = serial.Serial('COM11', 115200)  # Indicator, Year
ser2 = serial.Serial('COM13', 9600)  # Temperature
ser3 = serial.Serial('COM14', 9600)  # Vibration

# Initializes the display screen
region = ""

pygame.init()

# Set up the display
screen = pygame.display.set_mode((1600, 800))


class Button:
  def __init__(self, x, y, w, h, text, value):
      self.rect = pygame.Rect(x, y, w, h)
      self.text = text
      self.value = value

  def draw(self, screen, lb):
      if self.value == lb:
         color = (255, 189, 3)
      else:
         color = (43, 105, 86)
      pygame.draw.rect(screen, color, self.rect)
      font = pygame.font.Font(None, 36)
      text = font.render(self.text, 1, (255, 255, 255))
      screen.blit(text, (self.rect.x + 10, self.rect.y + 10))
      font = pygame.font.Font(None, 50)
      text = font.render("Region", 1, (0, 0, 0))
      screen.blit(text, (350, 100))
```

```
        font = pygame.font.Font(None, 50)
        text = font.render("Year", 1, (0, 0, 0))
        screen.blit(text, (1050, 100))

    def handle_event(self, event):
        if event.type == pygame.MOUSEBUTTONDOWN:
            if self.rect.collidepoint(event.pos):
                return self.value
        elif event.type == pygame.MOUSEBUTTONUP:
            return None
        return None


def read_Arduino():  # Reads the Year qnd indicator selected by the user.
    line = ser1.readline().decode('utf-8').strip()
    if line:
        indic = line
        return indic


def write(val):  # Writes new Value to Vibration and Temperature Arduino
    send = str(val) + '/n'
    ser2.write(send.encode())  # Comment to turn off temperature
    ser3.write(send.encode())  # Comment to turn off vibration


def play_sound(indic, cat):  # Plays a new sound if Indicator or value changes
    if indic != "0":
        winsound.PlaySound(r"C:\Users\luukw\OneDrive\Documents\GPSOUNDS\s_" + str(indic)
+ str(cat) + ".wav",
                           winsound.SND_LOOP + winsound.SND_ASYNC)
    else:
        winsound.PlaySound(None, winsound.SND_PURGE)


def get_text(indic):  # Converts acronyms to full indicator and region
    text = "Indicator: "
    if indic == "Prec":
        text += "Precipitation"
    elif indic == "ST":
        text += "Sea Temperature"
    elif indic == "AT":
        text += "Air Temperature"
    return text


def indicator_text(text):
    font = pygame.font.Font(None, 50)
    text = font.render(text, 1, (0, 0, 0))
    screen.blit(text, (800, 600))
```

```
def search_csv(reg, ye, indic):  # Checks the new value if any input changes and none of
them are empty
  if indicator != "0" and region != "" and year != "":
     data = pd.read_csv(r"C:\Users\luukw\OneDrive\Documents\GPCSV\CSV_" + str(indic) +
"_" + str(reg) + ".csv")
     data.set_index(data['Year'], inplace=True)
     val = data.loc[ye, 'Value']
     return val
  else:
     return 0


# Initialize values for the Pygame Screen
buttons = [
  Button(100, 200, 250, 50, "Antarctica", "AN"),
  Button(450, 200, 250, 50, "North Sea", "NS"),
  Button(100, 400, 250, 50, "Indonesian Sea", "IS"),
  Button(450, 400, 250, 50, "Greenland", "GL"),
  Button(275, 600, 250, 50, "East Bering", "EB"),
]

min_year = 1960
max_year = 2090
slider = pgw.Slider(screen, 800, 400, 600, 50, min=min_year, max=max_year, step=10,
colour=(90, 219, 181),
              handleColour=(43, 105, 86), handleRadius=25)
output = TextBox(screen, 1050, 500, 100, 50, fontSize=30)
output.disable()  # Act as label instead of textbox
# Main Loop - Always has to be true
running = True
while running:
  # First run the screen
  events = pygame.event.get()
  for event in events:
     if event.type == pygame.QUIT:
        running = False

     # Handle button events and get region
     for button in buttons:
        value2 = button.handle_event(event)
        if value2 is not None:
           region = value2
           break

  # Draw the buttons and text
  screen.fill((216, 230, 216))
  for button in buttons:
     button.draw(screen, region)
```

```
  # Year selection
  year = slider.getValue()
  output.setText(year)
  # Get the indicator
  indicator = read_Arduino()
  indicator_text(get_text(indicator))
  # Update the screen
  pygame_widgets.update(events)
  pygame.display.update()
  pygame.display.flip()

  # Operations for Actuations
  if indicator != prev_Indic or year != prev_Year or region != prev_Region:  # Only search the
CSV if a value changes
      value = search_csv(region, year, indicator)
      prev_Year = year
      prev_Region = region
      print(str(year) + " " + str(indicator) + " " + str(region))
  if value != category or indicator != prev_Indic:  # Change the sound if indicator or value
changes
      play_sound(indicator, value)
      prev_Indic = indicator
  if value != category:  # Only write to the Arduinos if the actuation data changes - Otherwise it
wastes operations
      category = value
      write(value)  # Comment to turn off vibration + temp
      print(value)
  time.sleep(0.001)  # Do not touch the delay - can break everything

pygame.quit()
```

Appendix E - Information letter

Information letter

TangiBits: Facilitating a data physicalization to convey ordinal data

Purpose and procedure

The purpose of this research is to evaluate the combinations of haptic and sonic modalities in a data physicalization based on data perception and user experience. For this goal, participants will interact with a data physicalization with the goal of answering a few questions about the dataset.
Before participants interact with the data physicalization, they will receive a short oral explanation on how it works, and after answering the questions about the dataset users will have an opportunity to provide further feedback to the researchers. The entire experiment will take around 25 minutes for each participant.

Benefits and risks

The project has been reviewed and approved by the EEMCS Ethics Committee. There are no mental or physical risks for participating with this experiment.

Withdrawal of study

Users consent voluntarily to be a participant in this study and understand that users can refuse to answer questions and users can withdraw from the study at any time, without having to give a reason. To withdraw from the study, users can contact one of the researchers at any point in time.

Personal information

Users understand that the data collection about personal information will not be shared beyond the study team. Personal information will not be used in any reports, and will be destroyed within 5 days of participation.

Data usage

The data will be collected through an online survey. The data types collected will be answers to the questions about the data, and the time it takes to answer the questions. The data will be used for this research and will be archived to be used in future research. All data collected will be anonymised completely within 5 days of participation, all personal information will be destroyed at this point.
The collected data will be used in two separate essays, and won't be published separately. Only the researchers and the supervisor will have access to the data.

Contact details

Below is the name of the researchers,
Researcher 1: Luuk Welling, L.K.Welling@student.utwente.nl
Researcher 2: Bima Ade Dharmaputra, bimaadedharmaputra@student.utwente.nl

Appendix F - Consent form

Consent Form for TangiBits: Facilitating a data physicalization to convey ordinal data

YOU WILL BE GIVEN A COPY OF THIS INFORMED CONSENT FORM

Please tick the appropriate boxes	**Yes**	**No**
Taking part in the study		
I have read and understood the study information dated 09-11-2023, or it has been read to me. I have been able to ask questions about the study and my questions have been answered to my satisfaction.	◻	◻
I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time, without having to give a reason.	◻	◻
I understand that taking part in the study involves personally filling in a questionnaire asking questions about data exploration and the experience with the installation.	◻	◻
Use of the information in the study		
I understand that information I provide will be used for two separate reports	◻	◻
I understand that personal information collected about me that can identify me, such as my name, will not be shared beyond the study team.	◻	◻
Future use and reuse of the information by others		
I give permission for the anonymised survey answers that I provide, and the error rate to be archived in Excel so it can be used for future research and learning.	◻	◻

Signatures

______________________ ______________________ _________

Name of participant Signature Date

I have accurately read out the information sheet to the potential participant and, to the best of my ability, ensured that the participant understands to what they are freely consenting.

_________________________ ___________________
____
Researcher name Signature Date

Study contact details for further information: Luuk Welling, L.K.Welling@student.utwente.nl

Contact Information for Questions about Your Rights as a Research Participant
If you have questions about your rights as a research participant, or wish to obtain information, ask questions, or discuss any concerns about this study with someone other than the researcher(s), please contact the Secretary of the Ethics Committee/domain Humanities & Social Sciences of the Faculty of Behavioural, Management and Social Sciences at the University of Twente by ethicscommittee-hss@utwente.nl

Appendix G - Preliminary form

Identification number	

Preliminary Questions

1. Which of these regions will have the largest predicted increase in Air temperature from 1960-2090?
   - ☐ The North sea
   - ☐ Antarctica
   - ☐ The Indonesian sea
   - ☐ The East Bering sea
2. Which of these regions has the most precipitation (Rain or snow) on average?
   - ☐ Greenland
   - ☐ The Indonesian sea
   - ☐ Antarctica
   - ☐ The East Bering sea
3. Which of these regions has the lowest sea temperature in 2022?
   - ☐ The North sea
   - ☐ Greenland
   - ☐ The East Bering sea
   - ☐ Antarctica
4. Which of these regions has the least precipitation?
   - ☐ The Indonesian Sea
   - ☐ Greenland
   - ☐ Antarctica
   - ☐ The North sea

Familiarization tasks

1. Compare the air temperature of the North Sea and Antarctica in 2060, which one is higher?

2. Compare the sea temperature of the East Bering in 2010 and 2050, which one has a higher temperature?

Appendix H - Categorization code

```
import pandas as pd
import jenkspy as jp
import numpy as np

n_breaks = 3  # Amount of categories

# Loading and reading the dataset
data =
pd.read_csv(r"C:\Users\luukw\Documents\Downloads\PrecCSV.csv")
#Load CSV file
data.head()
data['Date'] = pd.to_datetime(data['Date'])
#Convert to time series
data.set_index(data['Date'], inplace=True)
ts = data['Value']

# Converting data to list for algorithm
y = np.array(ts.tolist())


#Calculating the breaks and printing the values
breaks = jp.jenks_breaks(y, n_classes=n_breaks)
breaks_jkp = []
for v in breaks:
   idx = ts.index[ts == v]
   breaks_jkp.append(idx)
   print(v)
```