Multimodal Data Physicalization for Climate Change Communication: Exploration of Haptic and Auditory Modalities

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Abstract

Data physicalization is a technique of representing data in a physical interface, a new way to interact with data that can be perceived through human senses. Data visualization is an example of human-computer interaction representing data in graphical or visual forms that are easy to understand. This human-data interaction opens the door to exploring various modalities, such as haptic, auditory, physical, and visual. However, there is no research comparing different modalities in data physicalization. Therefore, this research aims to compare different combinations of temperature, vibration, and sound modalities in data perception and user experience of a data physicalization conveying climate change data using ordinal data.

This project uses three indicators to describe the change in global climate, land precipitation, air temperature, and sea temperature. Additionally, the scope of the data spans from 1960 to 2090 from across five regions: the Indonesian Sea, the East Bering Sea, The North Sea, Greenland, and Antarctica, providing a projection of the historical transformation of emission, the current state, and the potential future trajectory of our climate.

The user evaluation is conducted to find the efficiency, accuracy, mental load, and subject confidence between the combination of modalities: temperature and sound, vibration and temperature, and each modality separately to compare the perception of data. The study was designed as a between-subject user study to avoid the learning effect with 24 participants.

In conclusion, there is no significant difference in data perception among the combinations of modalities: temperature and sound, vibration and temperature, and each modality separately. However, the use of multimodal combinations, temperature and sound, vibration and temperature, and vibration and sound, enhance the overall user experience. For conclusive results on the impact of the combination(s) of modalities in data perception, it is recommended to repeat the study with a larger observation sample.

Keywords: Multimodalities; Data Physicalization; Temperature; Haptic; Auditory; Climate-change

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Table of Contents

List of Tables

List of Figures

Chapter 1 - Introduction

1.1. Introduction

Data physicalization is a technique of representing data in a physical interface [2], a new way to interact with data that can be perceived through human senses. The increasing advancements in human-data interaction open a way of representing data through tangible devices. Data visualization is an example of human-computer interaction representing data in graphical or visual forms that are easy to understand [21]. Spalburg et al. [1] claim that data visualization has proven to be highly effective in increasing the performance in understanding data complexity. This human-data interaction opens the door to exploring various modalities, such as haptic, auditory, physical, and visual. This potential enables ways of interacting with data and multisensory experience [3]. Jansen et al. [2] explain that data physicalization has shown cognitive benefits, enhancing sensorimotor skills, better data recall, active perception, and intermodal perception. Despite its benefits, more research on data physicalization techniques still needs to be explored. The research gap highlights the need for further exploration and evaluation of data physicalization. Additionally, there is no research comparing different modalities in data physicalization. Therefore, this research aims to compare different combinations of haptic and auditory modalities in data perception and user experience of a data physicalization conveying climate change data using ordinal data.

We chose climate change as the use case data to evaluate this research. The need to effectively understand environmental data has become urgent in the face of global climate change. Based on today's insufficient global commitments to reduce climate polluting emissions, it may push 2030 emissions even higher – up to 60 GtCO2e [25]. Climate change is driven primarily by human activities such as burning fossil fuels and changes in land use. These activities pose an existential threat to the earth, which leads to extreme temperature changes, melting ice caps, and rising sea levels. The IPCC report states that the global average temperature in 2019 was 1.1 degrees Celsius above the pre-industrial period and made 2019 the second hottest year on record [24]. The Intergovernmental Panel on Climate Change (IPCC) warns that without significant reductions in greenhouse gas emissions, we are on a trajectory towards irreversible damage with fatal implications for global ecosystems and human societies. The window of opportunity to restrain these impacts is narrowing, demanding rapid and decisive responses across sectors.

Additionally, there are four global climate indicators that can best describe the changes in global climate, which include land precipitation, Arctic ice coverage, air temperature, and sea temperature [8]. These indicators are interconnected, meaning that changes in one indicator influence the other indicators.

However, this project only uses three indicators, such as land precipitation, air temperature, and sea temperature, since we also want to observe five different regions. In other words, the Arctic ice coverage is not an indicator that can be found across different regions. The scope of the data spans from 1960 to 2090 from across five regions: the Indonesian Sea, the East Bering Sea, The North Sea, Greenland, and Antarctica, providing a projection of the historical transformation of emission, the current state, and the potential future trajectory of our climate based on a projection tool called CMIP6 [8].

The research gap in comparing multimodal data physicalization is the motivation to explore the combination of haptic and auditory modalities for global climate communication. This study explores the efficiency, accuracy, mental load, subjective confidence, and subjective preference of data physicalization in conveying global climate change data. Therefore, the research question is: ***How do different combinations of modalities: temperature and sound, vibration and temperature, and each modality separately, compare in data perception and user experience of a data physicalization conveying climate change data?***

Thus, the expected outcome of this study is to provide a ranking of combinations of modalities by assessing user experience and the perception of ordinal data in the context of climate change.

Chapter 2 - Related literature

The clear definition of data physicalization involves the representation of data using physical artifacts to convey information. This refers to the practice of translating data into physical forms [2] [3] [11]. However, there are various interpretations of data Physicalization based on different researchers. Jansen [2] describes the most well-known definition of data physicalization. She describes data physicalization as a physical artifact whose geometry or material properties encode data [2]. This definition became the foundation of data physicalization. It is commonly used in papers related to data physicalization. Building upon this fundamental concept, it is essential to recognize that encoding variables, the properties of the material used to encode data, have a significant role in designing multisensory and immersive data experiences.

2.1. Definition of modalities

After laying out the solid foundation of data physicalization, it is important to examine modalities. In the world of data physicalization, modalities are best described as sensory channels or modes of perception. Modalities are the ways humans perceive and interact using their senses. It includes touch, sight, smell, taste, sound, and dynamic changes over time. Seven categories are associated with specific modalities. Ranasinghe et al. [4] makes clear the definition of modalities, she identifies seven variables (big categories) that are used to encode information in diverse ways. It involves physical, visual, haptic, olfactory, gustatory, sonic, and dynamic variables.

Physical variables are variations of material properties that are used to encode data and are associated with the sense of touch and material properties—for example, smoothness, viscosity, and sponginess. Visual variables relate to how data is visually represented and associated with the sense of sight and visual perception—for instance, visual size, shape, and color. Haptic variables involve the sense of touch and tactile properties—for instance, vibration, pressure, temperature, and friction. Olfactory variables are related to the sense of smell—for instance, scent type. Gustatory variables are connected to the sense of taste. For instance, several types of tastes. Sonic variables involve the sense of hearing and sound perception to encode data through auditory experiences—for example, sound locations, loudness, pitch, and rhythmic patterns. The last one is dynamic variables, which represent change over time. For example, perception time and rate of change. Each of these variables is correlated with specific modalities.

2.2. Benefits and challenges of data physicalization

After establishing a basis in data physicalization and modalities, it is crucial to investigate the benefits and the challenges of data physicalization. Data physicalization is a promising approach for transforming data into physical objects, bridging the gap between people and data. Tangible representations of data offer cognitive benefits, including aiding self-reflection, enhancing attention, and providing easier data access. Jansen et al. [2] [20] explain that data physicalization can enhance complex sensorimotor skills, enabling efficient information extraction from the physical world. Consequently, it brings about advantages such as active perception, depth perception, engagement of non-visual senses, intermodal perception, and the integration of data into the real world [2] [3] [4] [5] [10] [16]. This immersive and tangible method has the potential to reach diverse audiences, including those who are traditionally hard to reach or individuals with disabilities [4]. Moreover, it opens up opportunities for increasing data comprehensibility and engagement, thereby supporting human decision-making through the use of physical representations and interactions.

However, alongside these benefits, it is important to also address the challenges of data physicalization. The design of data physicalization involves a vast design space, including material selection, interactions, and data encoding. Users are often faced with numerous options, making it a challenge to make informed design choices [11]. The other limitation focuses on the challenge that is usually faced by the creator. Creating data physicalization involves making many choices, like selecting materials, sizes, and how data is presented. With these choices, it can be tricky to decide what works best to convey certain information. Since data physicalizations often do not follow a standard way of showing data, this can make it hard for people to understand what they are looking at, unlike regular charts and graphs [11].

2.3. Related work

This research aims to explore various modalities for data physicalization. Therefore, reviewing related work is crucial to understand the data perception and user experience of multimodal representation. There are a few related works in data physicalization. First example is a research that was conducted to explore the use of vibration and temperature as ways to convey information about Sustainable Development Goals (SDGs) [10]. The study involved 16 participants who tested an installation to represent SDG 7, which focuses on affordable and clean energy. This installation created a heat map of five different countries, as shown in Figure 1. The project took out the visualization modalities to remove visual elements, so the participants can understand other modalities.

Figure 1. The heating map created by VanLoenhout [10]

It is proven that sight is the most valued sense [15]. Humans mostly rely on their vision to memorize and make decisions. This project took out the visualization modalities to really compare the effectiveness of vibration and temperature. The requirement for this installation was to allow users to choose between two modalities (vibration and temperature) and two datasets. The goal was to compare the effectiveness and efficiency of conveying information through vibration and temperature. Effectiveness was measured by the number of correct answers. At the same time, efficiency was determined by the time participants took to answer the questions after reading them [14].

A study titled 'CairnFORM: a Shape-Changing Ring Chart Notifying Renewable Energy Availability in Peripheral Locations' was conducted to explore the visualization of renewable energy availability using a shape-changing movement speed as the modality. This innovative installation utilizes dynamic physical ring charts to display forecasts of renewable energy availability in both public and workplace settings. Its goal is to increase awareness of renewable energy by physicalizing data forecasts through the dynamic alteration of its cylindrical form, employing various motions and speeds to represent energy data, as illustrated in Figure 2. The research assessed CairnFORM's effectiveness, usability, and user experience in conveying information on renewable energy movement across different environments. This study highlights the high effectiveness of its shape-changing capabilities for tasks such as identifying energy variation ranges and determining peak energy production hours, demonstrating that users can easily interpret the physical changes in CairnFORM to understand complex renewable energy data.

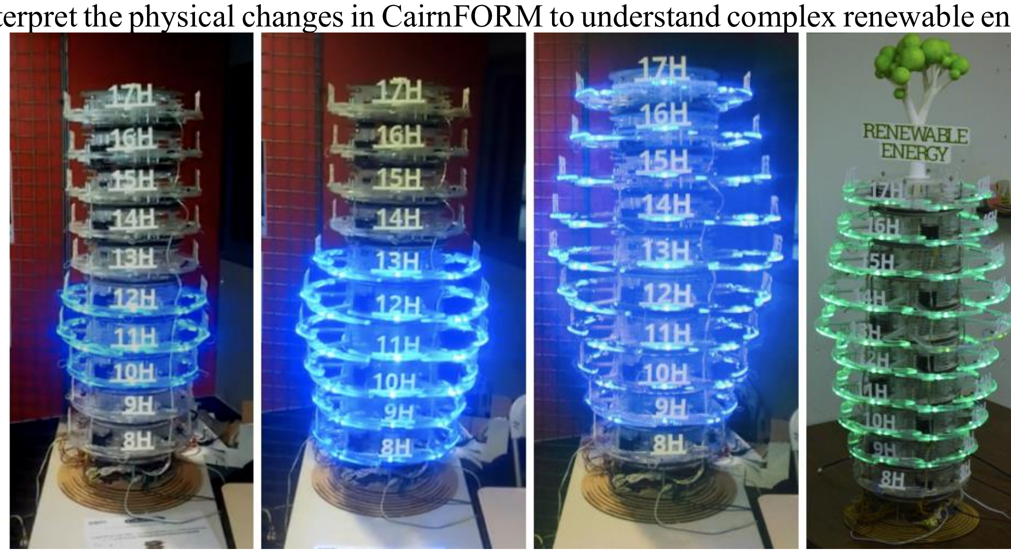

Figure 2. CairnFORM Installation [29]

2.4. Research Gap

Current studies comparing the impact of single modalities have provided us with essential insights into data physicalization, helping us understand how to convey use case data effectively and compare data perception and user experience between modalities. However, there remains a gap in research regarding the comparison of multimodal approaches for conveying use case data.

Chapter 3 - Methodology

3.1. Designing and implementing a data physicalization

This chapter outlines the methodological framework for studying the physicalization of global climate change data. The investigation involved meticulous data acquisition from the National Oceanic and Atmospheric Administration (NOAA) Physical Sciences Laboratory, explicitly focusing on land precipitation, sea temperature, and air temperature across five regions [22]. The Community Earth System Model (CMIP6) derived maximum values for land precipitation, sea temperature, and air temperature. The following section explains the conversion of this data into ordinal categories and the subsequent mapping onto physical actuators, namely module Peltier and vibration motors.

3.2. Design Requirements

The installation design needs attention to the system functionalities, user requirements, and outputs. These requirements should work smoothly to create an immersive and interactive experience through the tangible installation.

3.2.1. System Functionalities

- The system must indicate the five regions provided to the users: the East Bering Sea, Greenland, North Sea, Indonesian Sea, and Antarctica.
- The system must project the year slider to the users; the years included are from 1960 until 2090.
- The system must show the selected global climate indicator.
- The system must facilitate the combination of modalities.
- The system should not visually represent data.

3.2.2. User requirements

- Users must be able to select the desired global climate input indicator, such as land precipitation, sea temperature, and air temperature.
- Users should be able to change the input indicator in the middle of the experiment.
- Users should be able to select the year through the year slider.
- Users should be able to choose one of the 5 regions, that includes East Bering Sea, Greenland, North Sea, Indonesian Sea, and Antarctica.

3.2.3. Output requirements

- The system should be able to control communication from the selected user input to the Arduinos that control the actuators.
- The system must be able to show the correct data points.
- The system must be able to show the selected modalities.

3.3. Data Mapping of the global climate data

This research aims to convey not only historical transformations but also future projections of how much the climate could change in the coming years. These predictions are made using CMIP6 projection model [22], which brings together data from different climate models and SSP levels to predict different scenarios of the future.

The data from the CMIP6 model, as shown in Table 1, involves Shared Socioeconomic Pathways (SSP) to represent the global climate data. The SSP model is a set of scenarios in climate change research to explore potential future scenarios and their effects on greenhouse gas emissions and climate change. These scenarios, labeled SSP 1 through SSP 5, show different socioeconomic development based on assumptions regarding demographic, economic, social, technological trends, environmental conditions, and sustainability [27].

The data for the global climate indicators is collected from 1960 to 2090 across five regions with an average time gap of 10 years. The simulation uses historical emissions from 1960 to 2014 and SSP models for future projections from 2015 to 2090. The data mapping is taken from the maximum value of these three SSP models, which brings the results shown in Figure 3, Figure 4, and Figure 5. The dataset can be found in Appendix B.

Year (Period)	1960 - 2090
Time Average (Year)	10 Years
SSP Model	**SSP 1-2.6:** Represents a sustainability scenario with strict mitigation effort resulting in a radiative forcing level of 2.6 watts per square meter. **SSP 3-7.0:** Represents a middle-of-the-road scenario with moderate mitigation effort resulting in a radiative forcing level of 7.0 Watts per square meter. **SSP 5-8.5:** Represents a Fossil-fueled Development scenario with no significant mitigation effort resulting in a radiative forcing level of 8.5 Watts per square meter.
Global Climate Indicator	Land precipitation Sea temperature Air temperature
Regions	East Bering Sea, North Sea, Greenland Sea, Antarctica, and Indonesian Sea

Table 1. The setting to plot the dataset

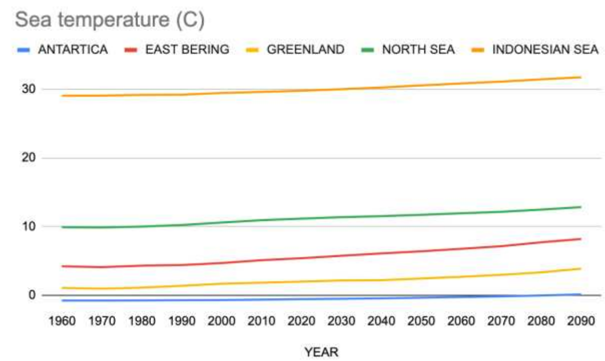

Figure 3. Plot of sea temperature in degree Celsius from 1960 - 2090

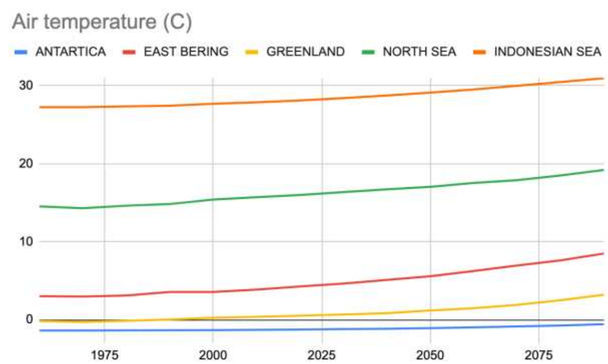

Figure 4. Plot of air temperature in degree Celsius from 1960 - 2090

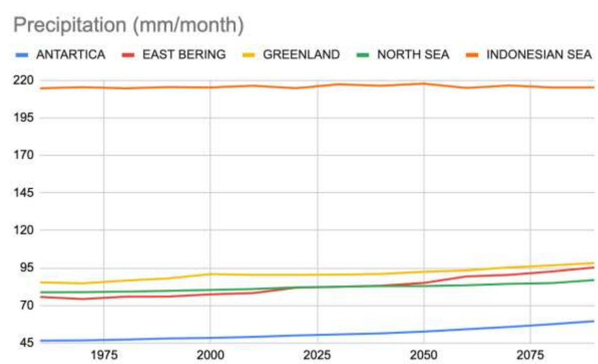

Figure 5. Plot of land precipitation in mm/month from 1960 - 2090

3.3.1. Translation to ordinal data

This section outlines the conversion from the raw data to ordinal data. The ordinal (global climate data) is divided into three categories: Low, Medium, and High. These three categories are calculated using the Jenks optimization method. The primary goal of Jenks optimization is to minimize the variance within each class while maximizing the variance between classes. This results in a classification highlighting natural patterns or data distribution breaks. The result from the Jenks optimization can be seen in Table 2 below. The categorized data can be found in Appendix C.

Category	Air Temperature (ºC)	Sea Temperature (ºC)	Land Precipitation (mm/month)
LOW	-1.4 - 8.5	-0.8 - 5.4	46.6 - 59.6
MEDIUM	8.6 - 20	5.5 - 12.9	59.7 - 98.4
HIGH	20.1 - 31	13 - 31.8	98.5 - 217.8

Table 2. Translated ordinal data

3.3.2. Translation to actuators data excluding sound

The following section highlights the conversion from ordinal data to the actuators. The actuators include a Module Peltier, a vibration motor, and headphones. The function of the Module Peltier is to generate heat. At the same time, the vibration motor is used to generate vibration.

The Module Peltier is encoded with PWM signals, as shown in Table 3. From the PWM signal, the digital signal is then converted into analog signal. In the end, the analog signal generates power for the Module Peltier to produce the heat.

Category	PWM Signal	Temperature (ºC)
LOW	240 (Reversed polarity)	-28.25
MEDIUM	120	33
HIGH	240	65.9

Table 3. Mapping ordinal data to temperature variable

For vibration, we used the full range of the vibration motors. Three vibration motors were used. The High category is the maximum intensity the vibration motors could actuate. The medium and low categories were then decided through trial and error: changing the value a few times and finding what was distinct enough to feel quickly. The vibration motor is encoded with PWM signals, as shown in Table 4. Similar as the Peltier module, the PWM signal is converted into an analog signal that controls the intensity of the vibration.

Category	PWM Signal	Vibration (RPM)
LOW	50	2500
MEDIUM	100	5000
HIGH	150	7500

Table 4. Mapping ordinal data to vibration variable

3.4. Evaluating the impact with users

Our evaluation focuses on several key aspects to assess the impact of different modalities on user perception and experience regarding data physicalization conveying climate change data.

Firstly, in evaluating user data perception, we consider two crucial components: efficiency and accuracy. Accuracy is determined by the number of correct answers provided by users. At the same time, efficiency is measured by the time users take to respond to each question.

In addition to data perception, we assess user experience through subjective confidence and mental demand. Users rate their confidence from a scale of one to five in their previous answers, allowing us to measure the perceived confidence in the information conveyed through single or combined modalities. Furthermore, users indicate the level of mental demand required to find answers, providing valuable insights into the cognitive load associated with each modality.

Chapter 4 - A data physicalization for representing data using Haptic and Auditory modalities

4.1. Hardware Components

The hardware infrastructure is the tangible foundation that translates climate data into perceptible and immersive experiences. The temperature and vibration are represented in haptic modality to represent data. Meanwhile, the rhythmic and tempo of sound generation from audio output devices are represented in the auditory modality. The installation uses three Arduino Uno to control the input and output.

4.2. Input

The input is reserved for the RFID to be the installation indicator. The input indicator allows users to select one of the three global climate data. The input indicator works with scanning the RFID to the RFID scanner that is connected to the Arduino Uno as shown in Figure 6.

- *Component:*
  1x MFRC522 RFID ,
  1x Arduino Uno Microcontroller.

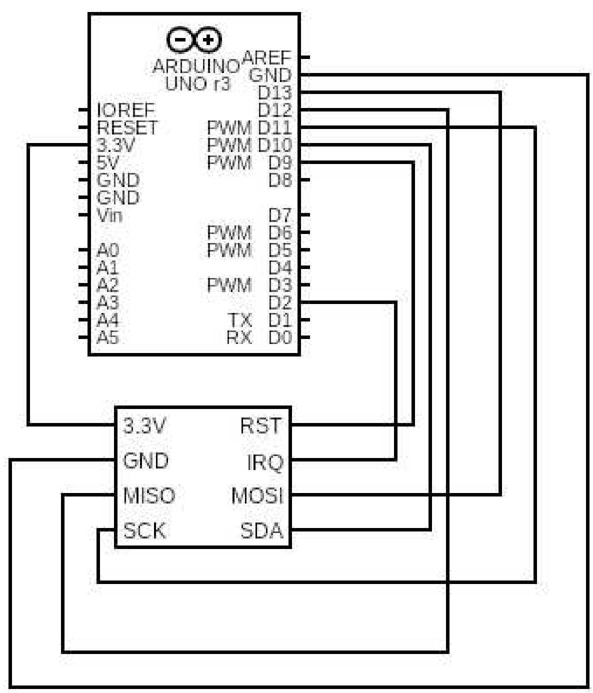

Figure 6. Schematic diagram of the input indicator

4.3. Output

The output of the installation consists of three different outputs. There are three Arduino Uno that are responsible for the outputs. The outputs create an immersive and tangible experience for data physicalization. These outputs are generated after selecting a year, an input indicator, and a region.

4.3.1. Temperature

The Peltier module acts as the heat generator. The Peltier module itself is reversible in the sense that they can heat on either side. The Peltier effect can explain it. In this phenomenon, an electric current passes through two different conductors. As a result, heat is absorbed or released at the junction [23]. Using an H-bridge with a Peltier module provides a way to control the heat from cold to hot. It can be achieved by connecting the Peltier plate to a relay. The following components are needed to build the circuit.

- *Components:*
  1x TEC1-12706 Thermoelectric Cooling Module with Peltier Element,
  1x 4 channel Relay,
  1x N channel MosFet,
  1x 10k resistor,
  1x 1k resistor.
- *Additional:*
  1x Power Supply with 12 V and 2 A,
  1x Arduino Uno Microcontroller,
  1x Heat sink,
  1x Thermal glue,
  1x Breadboard.

The Peltier plate is placed on top of the heat sink with the assistance of thermal paste. The heat sink helps to accelerate the heat dissipation. The placement of these components are located below a square canvas. It takes 6 seconds for the heat to transfer from one point to get to the right point. The schematic diagrams in Figure 7 and Figure 8, helps to prepare in building the circuit.

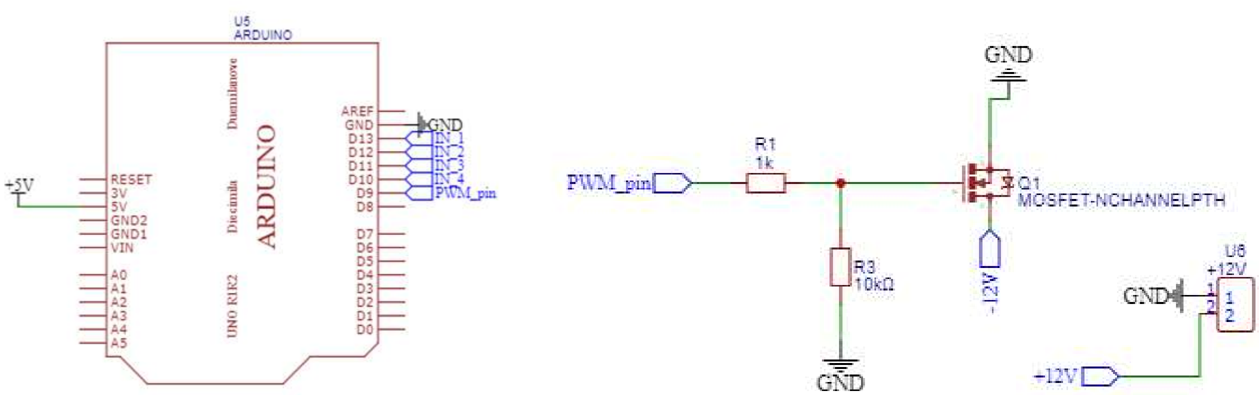

Figure 7. Circuit diagram of the Arduino connection with MOSFET and power supply

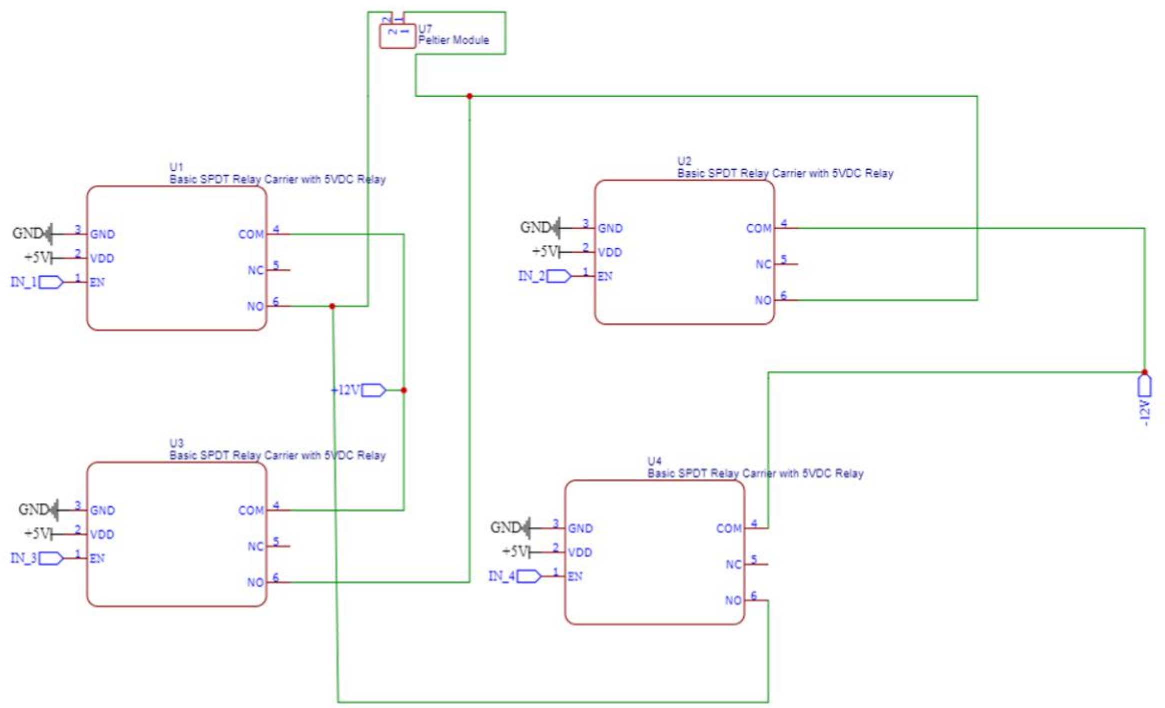

Figure 8. H-bridge Circuit diagram for the Peltier module

4.3.2. Vibration

In this setup, vibration motors help to stimulate users with experience of vibration. The placement of these three coreless motors are glued beneath a square canvas. The following components are needed to build the circuit.

- *Components:*
  3x NPN MosFet,
  3x 7500 RPM KPD7C-0716 coreless vibration motors.
- *Additional:*
  1x Breadboard
  1x Arduino Uno Microcontroller

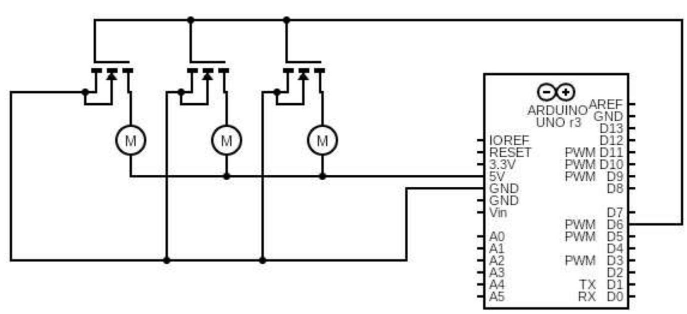

Figure 9. Circuit diagram of the vibration motors and Arduino Uno

4.3.3. Sound

Three different types of sound and tempo are responsible for evaluating the auditory modality, as shown in Table 5. The sound and the tempo correspond to the type of input indicator and global climate category (Low, Mid, High) respectively. The sound comes out from the connected Bluetooth headphones. Each sound type has three different clips, which in total there are nine sound clips and these nine sound clips are stored locally on the laptop.

Type	Sound type	Tempo (BPM)
Sea Temperature	Ocean waves	120
Land Precipitation	Rain drops	240
Air Temperature	Wind chimes	360

Table 5. Mapping value for sound variable

4.4. Software Components

In order to achieve the goals of this experiment, software components become one of the cores of this experiment. By optimizing the serial communication between three Arduinos and Python, users can experience the immersive effects of the heat generator, vibration motors, and sound corresponding to their chosen input. Arduino IDE and Python IDE are used for optimizing the actuators.

4.4.1. Arduino IDE

The Arduino used for the input indicator (RFID) and output actuators (heat generator and vibration motor) is programmed with C++ code. All Arduinos are connected to a laptop and establish communication through serial connection.

4.4.2. Python

When a user chooses a new indicator by placing it on the RFID reader, the selected indicator is sent to Python via serial communication. Python then checks if a region and a year have also been selected. If all three variables are chosen, Python opens the related CSV file, extracts the category (Low, medium, or high), and sends this category to the temperature and vibration Arduino. At the same time, Python uses the new category and the selected indicator to play the appropriate sound. Both the 9 sound clips and the 15 CSV files are stored locally on the laptop, so the system functions work without an internet connection.

4.5. Serial communication and architecture

The communication of our system can be explained in Figure 10. The selected data, including input indicator, year, and region, are sent to the software Python (central communication). Python extracts the categorized data and finds the corresponding data based on the chosen input. Python retrieves the data and sends it to the output Arduinos. The code for the communication between python and Arduino can be seen in Appendix D. At the end, the actuators are triggered with the chosen value.

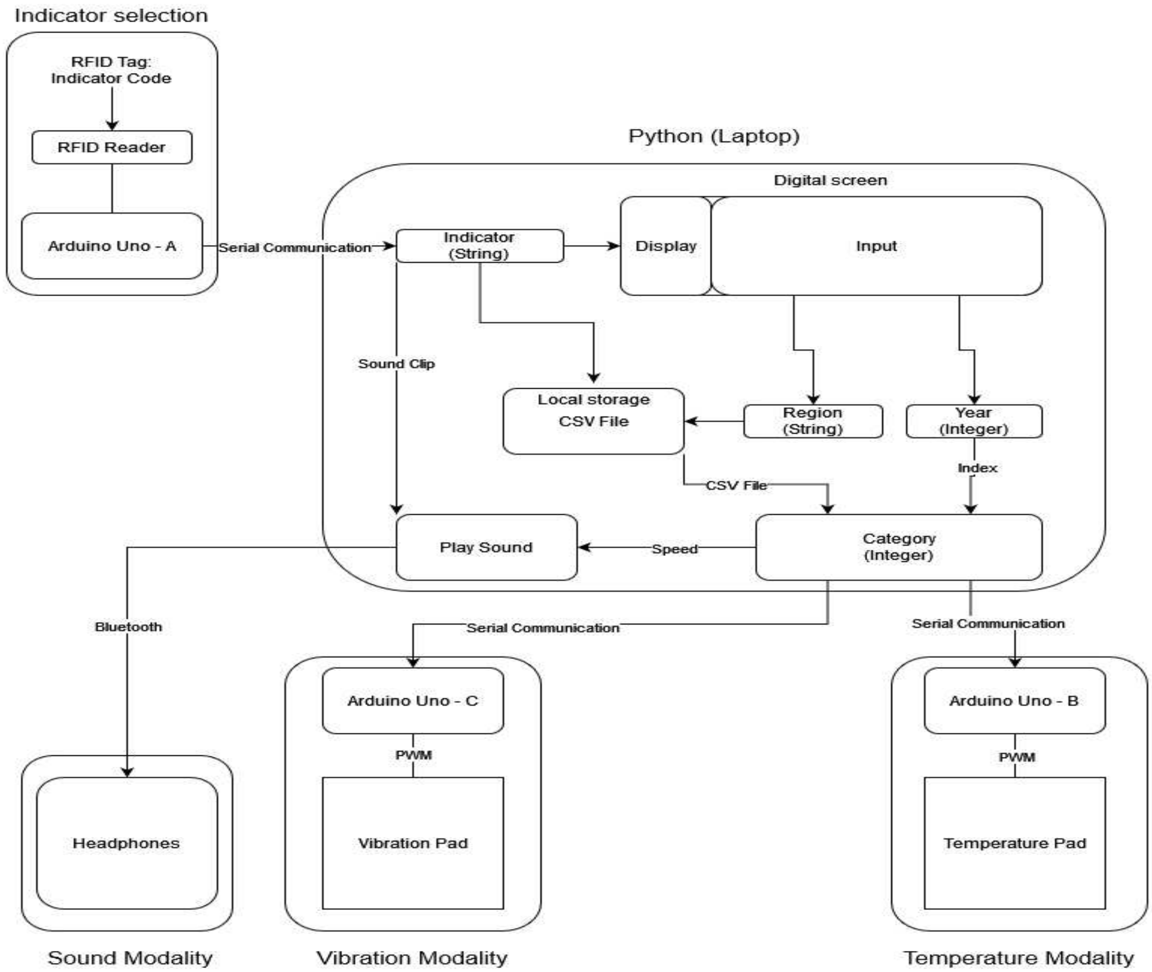

Figure 10. System communication of the installation

4.6. Final Setup

The final setup consists of two actuators (vibration motor and Peltier module) that are placed beneath the square canvas. There are three input indicators shaped in three different 3D models, it includes land precipitation, air temperature, and sea temperature. These indicators can be placed on top of the RFID scanner to register which indicator is selected, as shown in Figure 11. The selected indicator can be seen on the screen. The screen consists of selected indicators, year slider, and five regions.

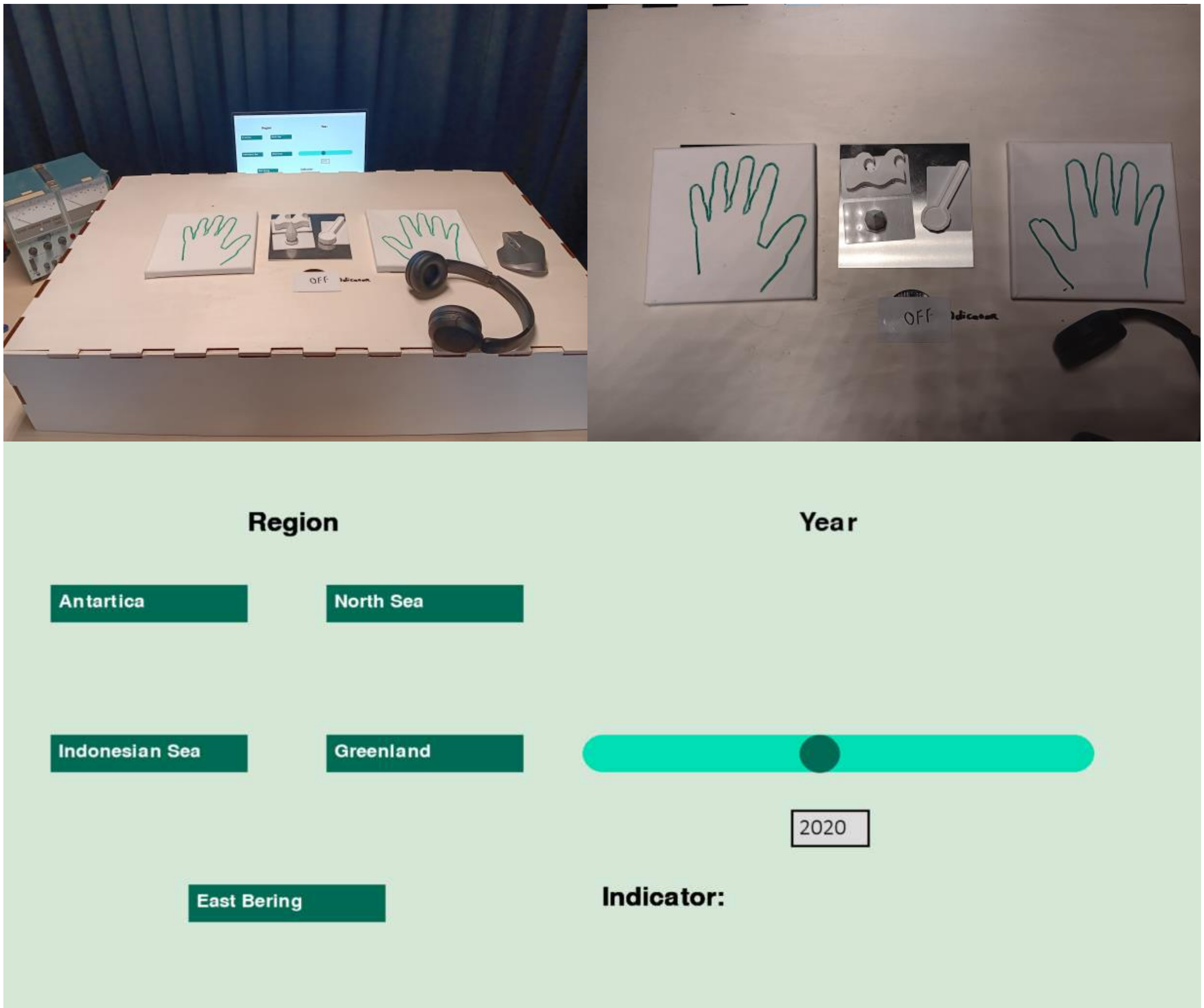

Figure 11. Final setup of the installation

4.7. Experiment

To activate the installation, there are three steps that the users need to do. The step begins with selecting an input indicator, a year, and a region. Then, the screen will show the selected indicator, selected year, and selected region. The user will then feel the sensation of haptic and auditory modalities by placing their hands on the canvas and putting on the headphones.

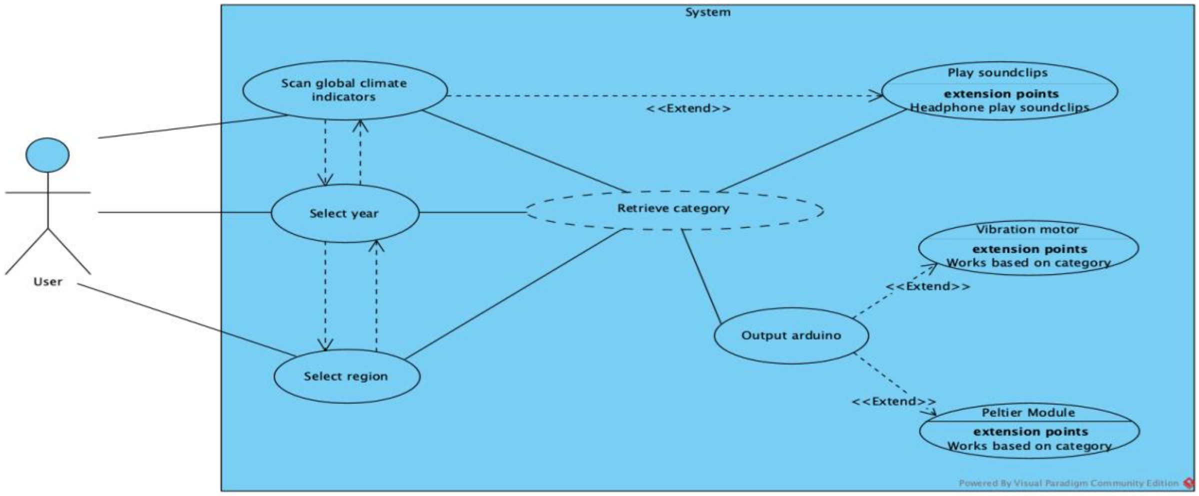

Figure 12. Use case diagram

Chapter 5 - Evaluation

5.1. Experimental Design

This chapter explains how we conducted the study to compare the effects of various combinations of modalities on people's understanding of climate change data through physical representation. It outlines all the necessary steps before and after the experiment, including selecting independent variables, measuring dependent variables, and the procedure. This design helps as a plan for our research study, guiding the implementation of the experiment and ensuring that the results are clear and understandable.

5.2. Goal of experiment

The goal of the experiment is to find out which of the different combinations of modalities works best for conveying climate change data and to provide a ranking of the different modalities based on efficiency, accuracy, mental load, and subjective confidence.

5.3. Study Design

To avoid the learning effect, the study will be a between-subject design, where participants will be exposed to a single combination of modalities. The three types of questions will be counterbalanced using a Latin square design to minimize concerns for internal validity.

5.4. Variables

The study was designed as a between subject user study, where each user experiences a single modality or combination of modalities to avoid the learning effect. This means the combination of modalities is the independent variable for our study, the dependent variables are accuracy, efficiency, mental load, subjective confidence in their answers and subjective feedback.

5.4.1. Dependent Variables

The outcome variation that is being studied includes efficiency, accuracy, mental load, subjective confidence, and subjective feedback. The dependent variables are measured on ordinal level. Table 6 explains how to measure the dependent variables.

Dependent variables	Measuring Technique
Accuracy	The number of right answers users give in the climate change data questionnaire.
Efficiency	The amount of time users take to answer each question in the questionnaire.
Subjective Confidence	A scale from 1 - 5 of how confident users feel in their answer.

Mental Load	Using the NASA TLX scale adapted to a range from 1 to 10 to answer the following questions: 1. How much mental demand was required? 2. How much mental and perceptual activity was required? 3. Was the task easy or demanding, simple or complex?
Subjective Feedback	Scanning the additional comments provided by the participants.

Table 6. The dependent variables and the measuring techniques

5.4.2. Independent Variables

The independent variables can be best described as the modalities variables, representing either single sensory inputs or combinations of sensory inputs that users will be exposed to. The list of independent variables is shown in Table 7. The context of choosing these independent variables is based on the use case data being used in this project. Climate change is the use case that we use as the data representation in data physicalization. In this project, three global climate indicators are determined, which include land precipitation, air temperature, and sea temperature. Provided that this experiment requires us to physicalize data, this research utilize temperature

Nr.	Independent variables
1.	Temperature and Sound
2.	Temperature and Vibration
3.	Vibration and Sound
4.	Temperature
5.	Vibration
6.	Sound

Table 7. List of independent variables

5.4.3. Controlled Variables

These variables are intentionally kept the same or controlled during the experiment to avoid affecting the dependent variable(s). Controlled variables include elements such as the environment, climate change questions, climate change datasets, and consistent instructions on how to use the setup.

5.4.4. Subjective Variables

Subjective variables are characteristics that vary across participants. The variables are the age of the participants and their pre-knowledge about climate change. To evaluate user’s pre-knowledge about climate change, we need a tool to measure their prior knowledge. To do this, there's a form users have to fill out before moving on to the next task. This form is called the preliminary knowledge form Appendix E.) and consists of four questions about climate change. Based on this form, we calculate the number of correct answers out of these four questions. From here, we can understand users' baseline understanding of global climate change.

5.5. Participants

24 participants are recruited through word of mouth and social media, the only important requirement is that participants speak English as the experiment will be conducted in this language.

5.6. Procedure

For the study, two researchers and one participant will be present at a time, the time for each participant will be around 25 minutes. Figure 13 explains the experiment procedure that the user will go through. Participants will first get a small explanation of how the installation works and what the goal of the experiment is and will fill in a small form about their knowledge about climate change data. After the participant fills in the consent form, the experiment starts. The consent form can be found in Appendix A. The user will get a form with 6 questions about the dataset, and questions about how confident they feel in their answer. After the questions are completed, the user will answer two more questions: One about the mental load, and one about further feedback.

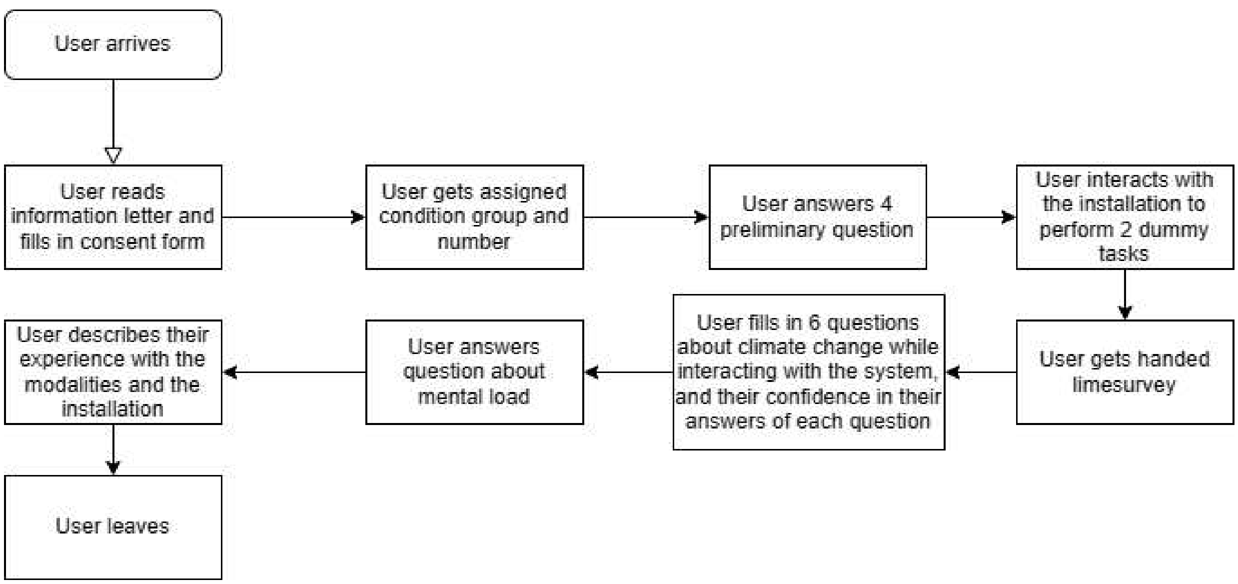

Figure 13. The experiment procedure

5.6.1. Apparatus

Participants will stand in front of the installation and will interact with different input options: climate indicator, year, and region. Additionally, they will experience the specific combination of modalities assigned to their group. Through Lime survey, the researchers will measure the time participants take to answer questions. Afterwards, the error rate of the answers will be calculated.

NASA TLX will be used to evaluate the mental load, and subjective confidence will be measured by asking users how confident they are in their answers on a scale from 1 to 10.

5.7. Tasks

Task 1 - <u>Preliminary task</u> (5 minutes): Participants will fill a consent form and preliminary knowledge questions form. The preliminary knowledge form can be found in Appendix E.
Task 2 - <u>Explanation</u> (5 minutes): Participants will receive a short oral explanation on how the installation works, (let them use it - dummy tasks)and what they will have to do and fill in a few questions about their knowledge on climate change data. The users will them sign the consent form
Task 2 - <u>Exploration</u> (15 minutes): Users will receive a form with 6 questions about the data, they will explore through the dataset to find the answers to the questions and submit these answers. Users will fill in the questionnaire form on an iPad.
Task 3 - <u>Evaluation</u> (5 minutes): Users will fill in the final question about the perceived mental load and will have an opportunity to give subjective feedback.

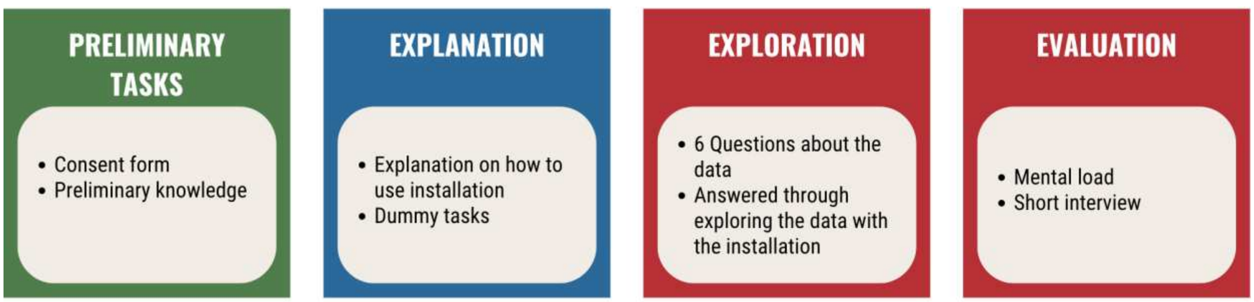

Figure 14. List of tasks that the participants need to go through

5.8. Questionnaire

These are the 6 questions that the participants need to answer in the lime survey. There are three types of questions: ranking, identifying, and comparing.

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?*
After each question, users will answer the following question:
Subjective confidence question: *How confident do you feel in your answer?*

5.9. Results

Twenty-four participants participated in the user evaluation. There were four participants assigned to each condition, meaning there were six conditions to evaluate the impact of the combination(s) of modalities in data perception and user experience. This section presents the findings of both quantitative and qualitative analyses. The quantitative analysis involves examining, efficiency, accuracy, mental load, and subjective confidence. Additionally, the qualitative analysis involves analyzing the subjective feedback provided by the users.

5.9.1. Efficiency

In order to analyze the efficiency of our installation, we measure it by the time the user takes to answer each question on the lime survey. The participants took, on average, 68,64 seconds with 18 seconds standard deviation in all conditions. Figure 15 shows that the average time participants spent answering each question in the combination of temperature and vibration group is the highest compared to other conditions, which took 92 seconds on average. In contrast, participants took on average 47.5 seconds to complete each question in the combination of vibration and sound group, which makes it the most efficient condition. It also shows that the single or combination of temperatures results in a lower efficiency compared to other modalities, making it the least efficient in the study.

Figure 15. The time participants spent answering each question on the LimeSurvey between condition groups (all condition(s), combination(s) of temperature group, combination(s) of vibration group, and combination(s) of sound group)

Shapiro-Wilk's test on normality is conducted to find out if the data is normally distributed for the efficiency between all conditions, with the following hypotheses:
H0*:* *"The data is normally distributed."*
H1*:* *"The data is not normally distributed."*

The null hypothesis is true with a 95% confidence interval, if the $p-value\ for\ all\ conditions\ >\ \alpha, with\ \alpha = 5\%$. Table 8 shows that the p-value for all conditions except vibration has a p-value that is greater than 5%. Therefore, we fail to reject **H0** at a 95% significance level in all conditions except vibration. Meanwhile, the p-value in the vibration condition is 0,037. The p - value for vibration is less than 5%, so we must reject **H0**. The significant difference is only found in vibration conditions. Additionally, the data of all conditions except vibration is normally distributed.

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

Table 8. Shapiro-Wilk's test on normality

After failing to reject the normality test. Then, the Kruskal-Wallis H test is conducted to evaluate if the distribution of efficiency is equal across all conditions, with the following hypothesis:
H0: *"The data distribution of efficiency is equal across the conditions."*
H1*:* *"The data distribution of efficiency is unequal across the conditions."*

As shown in Table 9, the p-value from this test is 0,087. Additionally, the p-value of all conditions > 0,05, with a 95% confidence interval. Therefore, we fail to reject the null hypothesis. Hence, the data distribution of efficiency is equal across the conditions.

Test Statistics[a,b]

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

a. Kruskal Wallis Test

b. Grouping Variable: VAR00001

Table 9. Kruskal-Wallis H test results for efficiency

In addition, Figure 16. The time participants spent answering each LimeSurvey question to compare single modalities and combination modalities study groups compares the efficiency between single modalities and combination modalities. It shows that participants took on average 74 seconds to answer each question using multimodal. In comparison, single modalities resulted in a shorter average response time. Participants took on average 63.24 seconds.

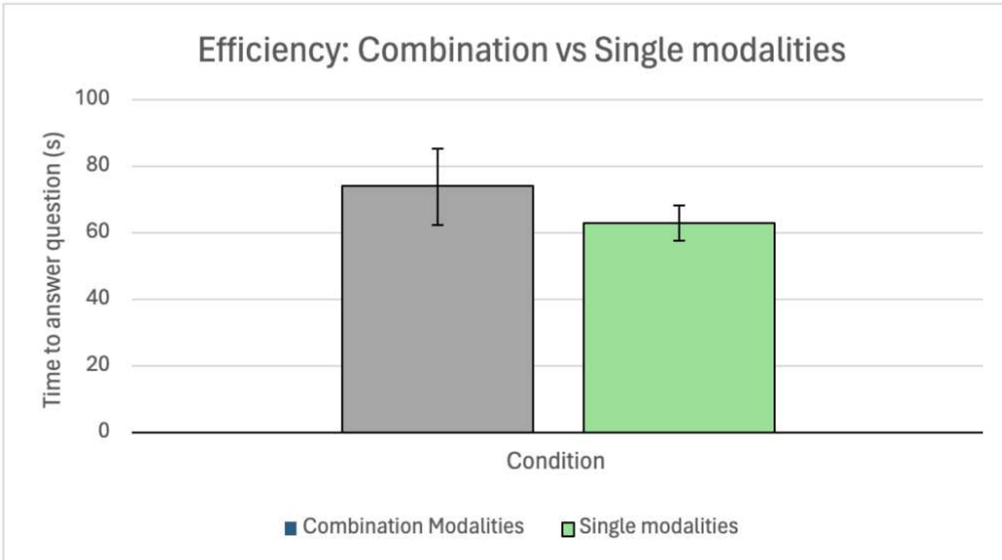

Figure 16. The time participants spent answering each LimeSurvey question to compare single modalities and combination modalities study groups

To compare the efficiency between combination modalities and single modalities, we conduct tests of normality with Kolmogorov-Smirnov and Shapiro-Wilk. Based on Table 10, "No" represents the group using single modalities and "Yes" represents the group using combination modalities. The hypothesis for this following tests are:

H0: *"The population is normally distributed"*

H1: *"The population is not normally distributed"*

Based on the result from SPSS from Table 10, the $p - value\ for\ single\ modalities$ is 0,103. The result shows that $p - value\ for\ single\ modalities > \alpha$, with $\alpha = 5\%$. So, we fail to reject the assumption of normal distribution. However, the $p - value\ for\ combination\ of\ modalities = 0{,}02 < 5\%$. Therefore, the null hypothesis is rejected. In conclusion, the data is normally distributed in single modalities and the data is not normally distributed for combination of modalities.

Tests of Normality

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

a. Lilliefors Significance Correction

Table 10. Shapiro-Wilk and Kolmogrov-Smirnov test result for the efficiency

Furthermore, to test if there is a significant difference in the combination of modalities condition, a Mann-Whitney test was used. According to Table 11, $p - value = 0{,}977 > 5\%$. The observed value is much bigger than 5%, meaning that the data distribution of efficiency is the same across categories of combinations normally distributed.

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.

Table 11. Mann-Whitney U test results for the efficiency

5.9.2. Accuracy

The number of correct answers from climate change questions is the way to analyze the accuracy of the single or combination modalities in conveying ordinal data. On average, the number of correct answers is 22 out of 24 for each condition. As shown in Figure 17, temperature and the combination of sound and temperature has the highest accuracy, which scores 23 correct responses. On the other hand, sound alone as a single modality shows only 20 correct responses, which makes sound as the modality with the lowest accuracy.

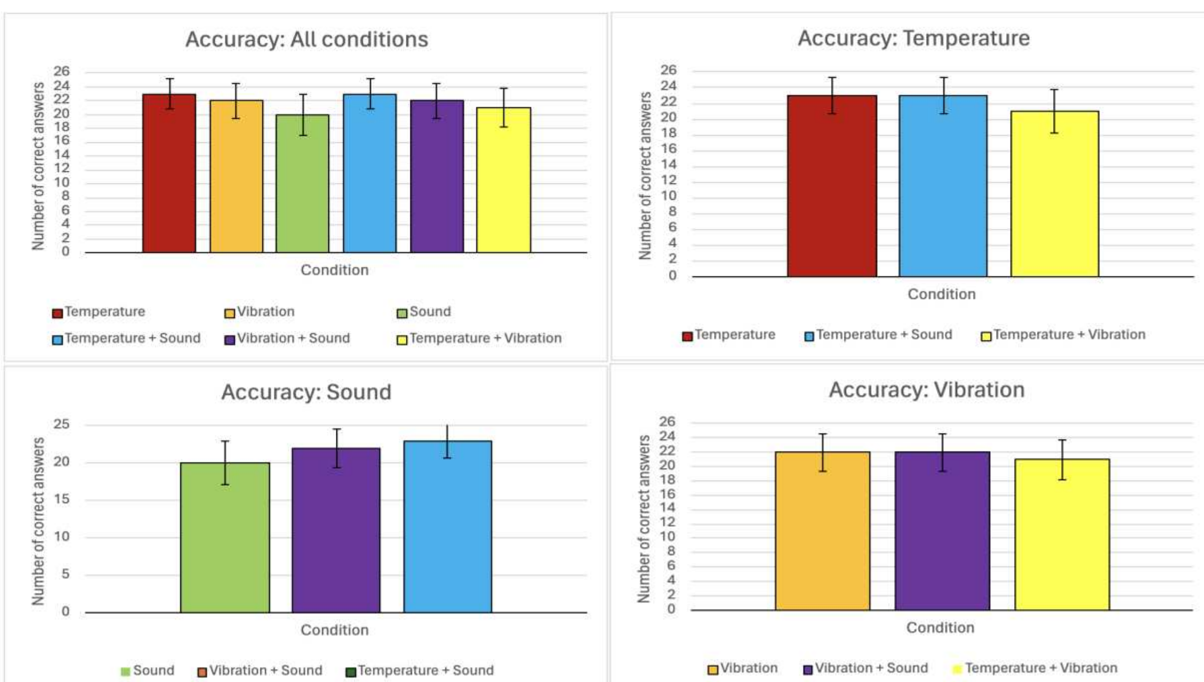

Figure 17. The amount of correct answers between condition groups (all condition(s), combination(s) of temperature group, combination(s) of vibration group, and combination(s) of sound group)

Again, the Shapiro-Wilk's test on normality is conducted to find out if the data is normally distributed for the accuracy between all conditions, with the following hypotheses:
H0*:* *"The data is normally distributed."*
H1*:* *"The data is not normally distributed."*

Table 12 shows the data is normally distributed for sound as a single modality, and the combination of vibration and temperature as multimodal. While, the other single / multi modalities must reject **H0**. That means the data is not normally distributed.

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

Table 12. Shapiro-Wilk's test on normality

Further tests are needed to investigate if there is a significant difference in accuracy. The $p-value\ of\ the\ accuracy\ of\ all\ conditions = 0.656 > 5\%$. Thus, the test fails to reject the null hypothesis that the data is normally distributed.

Test Statistics[a,b]

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

a. Kruskal Wallis Test

b. Grouping Variable: VAR00001

Table 13. Kruskal-Wallis H test results for accuracy

Additionally, Figure 18 shows the accuracy between single modalities to combination modalities. There is a slight difference between the accuracy of combination modalities to single modalities. Where the combination of modalities gathers 66 correct answers and the single modalities gets 65 correct answers out of 72 questions.

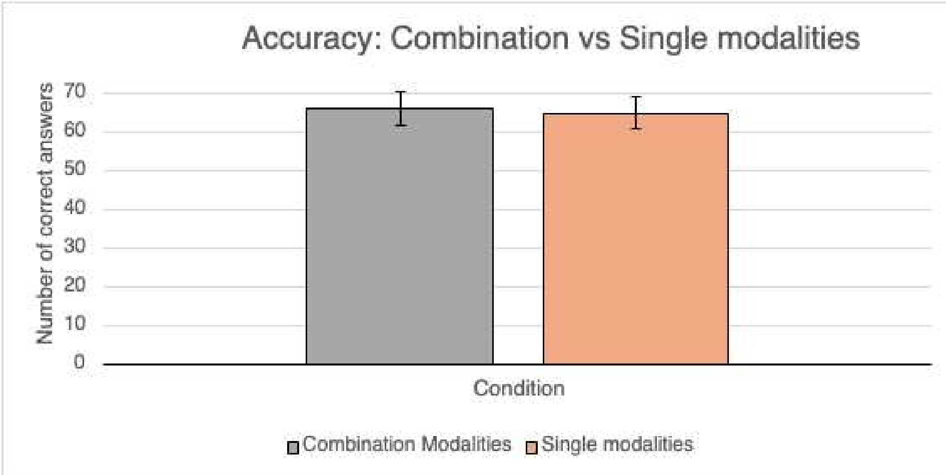

Figure 18. The amount of correct answers in answering each LimeSurvey question to compare single modalities and combination modalities study groups

To test the normality in the distribution in accuracy between single / multi-sensory modalities. Kolmogorov-Smirnov and Shapiro Wilk tests are conducted. The result of the $p - value\ in\ accuracy$ for both single and combination modalities $< 0{,}05$. Therefore, the result of the test must reject the hypotheses of normal distribution in accuracy.

Tests of Normality

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

a. Lilliefors Significance Correction

Table 14. Shapiro-Wilk and Kolmogrov-Smirnov test result for the accuracy

In addition, a further test to find out if there is significant difference in accuracy between individual / multiple modalities. Table 15 shows that the p-value is greater than 0,05, which means we fail to reject **H0**. Therefore, the distribution of accuracy is the same across categories of combinations.

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.

Table 15. Mann-Whitney U test results for the accuracy

5.9.3. Mental load

An adapted scale of NASA TLX, using a scale from 1 - 10, was used to measure how much mental demand was required in the decision-making. The average required mental demand based on these 24 participants is 5,62. The combination of vibration and temperature has the highest mental demand that was required in finding the answers, with a scale rate of 6,2, as shown in Figure 19. On the other hand, temperature, sound, and sound temperature have the same average mental demand, showing 5 as the mental demand.

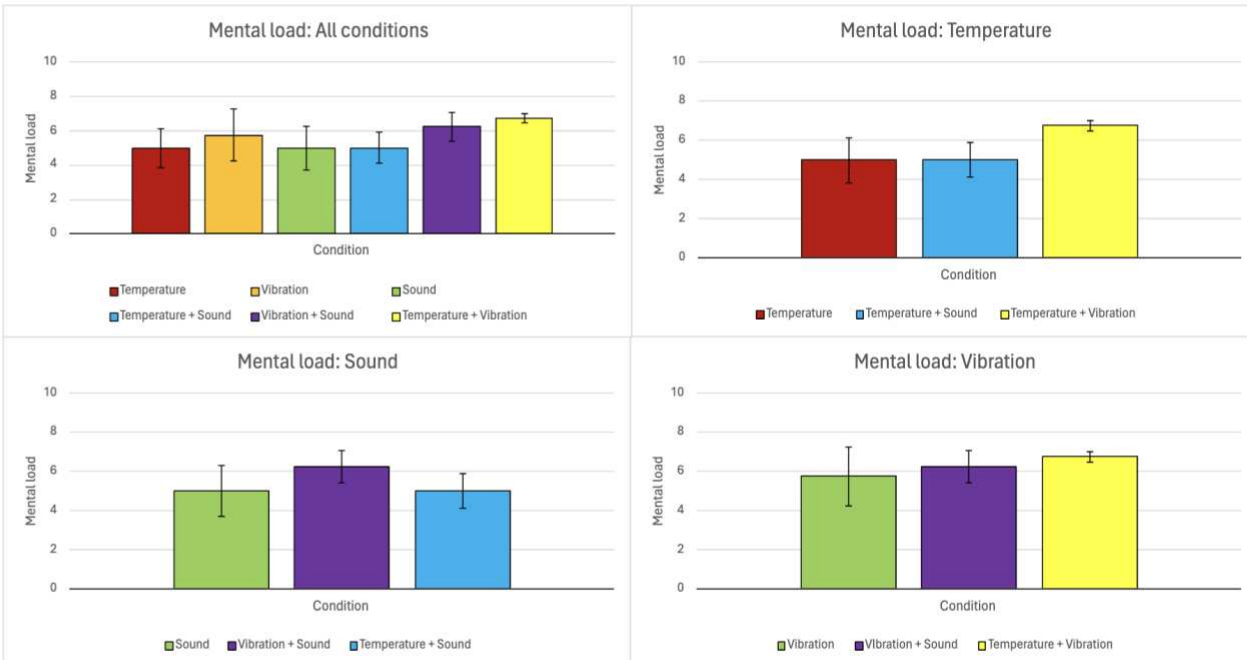

Figure 19. The mental load in interacting in finding the answers in the LimeSurvey between condition groups (all condition(s), combination(s) of temperature group, combination(s) of vibration group, and combination(s) of sound group)

After that, to analyze if the mental load data is normally distributed. Shapiro-Wilk's test on normality is conducted to find out if the mental load is usually distributed between all conditions, with the following hypotheses:

H0: *"The data is normally distributed."*
H1: *"The data is not normally distributed."*

Since the p-value of temperature as a single modality and the combination of vibration and temperature is less than 5%, with a 95% confidence level, as shown in Table 16, we can reject

H0. Thus, through Shapiro-Wilk's test, the data is not normally distributed in temperature and combination of vibration and temperature conditions.

Tests of Normality

	Condition	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		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

Table 16. Shapiro-Wilk and Kolmogorov-Smirnov test on normality

Then, we conduct a Wallis H test to find if the mental load is equal across all conditions. As Table 17 depicts that the $p - value\ of\ mental\ load\ >\ 0{,}05$. This means that the test fails to reject the null hypothesis. Therefore, there is no significant difference across 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

Table 17. Kruskal-Wallis H test results for mental load

Furthermore, the graph on Figure 20, shows that the mental demand required in combination modalities is higher than the single modalities. It is shown that the scale points to a mental load of 6 for the combination modalities. On the other hand, the single modalities have a mental demand of 5,25 points.

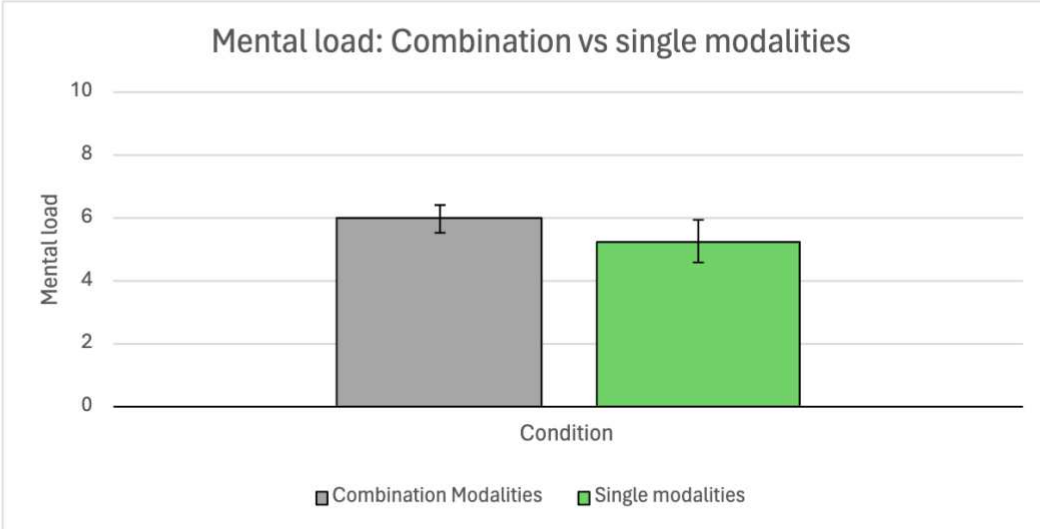

Figure 20. The mental load in answering each LimeSurvey question to compare single modalities and combination modalities study groups.

Shapiro-Wilk and Kolmogorov-Smirnov tests are conducted to compare the mental load between single modalities and a combination of modalities. With a 95% confidence interval, α= 5%. Table 18, shows that the result of single modalities from the test fails to reject the **H0**, since the p - value is greater than 0,05. However, the mental demand from the combination of modalities has a p-value = 0,045, which makes it slightly less than 0,05. Therefore, the test rejects the null hypothesis that there is no significant difference between the combination of modalities.

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

Table 18. Shapiro-Wilk and Kolmogrov-Smirnov test result for the mental load

Additionally, a Whitney U test is conducted after failing to pass the Shapiro-Wilk test on normality. Table 19 shows that the p-value = 0.478. Therefore, the p-value < 0,05, we fail to reject the null hypothesis. Hence, the distribution of mental load is the same across categories of combinations.

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.

Table 19. Mann-Whitney U test results for the mental load

5.9.4. Subjective confidence

Subjective confidence is measured on a Likert scale ranging from 1 to 5, with 1 representing 'extremely not confident' and 5 representing 'extremely confident.' As illustrated in Figure 21. The subjective confidence between condition groups (all condition(s), combination(s) of temperature group, combination(s) of vibration group, and combination(s) of sound group), the average confidence levels across all conditions range from 4 to 4.6 on the Likert scale, indicating that participants are generally confident to extremely confident.

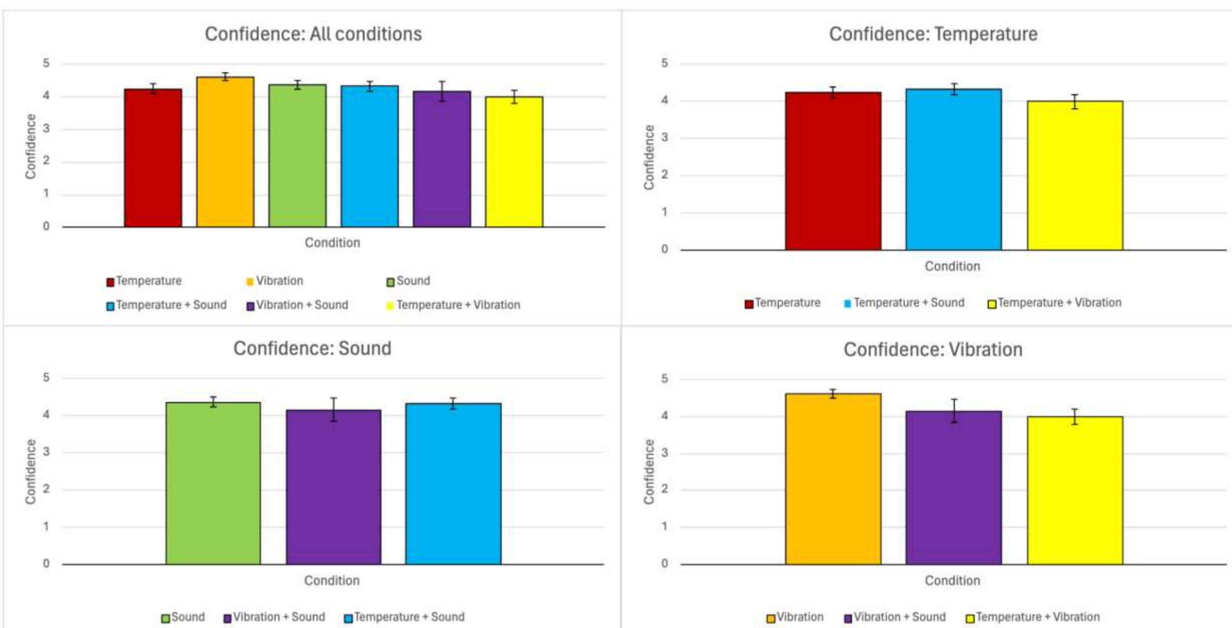

Figure 21. The subjective confidence between condition groups (all condition(s), combination(s) of temperature group, combination(s) of vibration group, and combination(s) of sound group)

The tests of Shapiro Wilk on normality is conducted to test if the confidence is normally distributed between all conditions, with the following hypotheses:

H0: *"The confidence is normally distributed"*

H1: *"The confidence is not normally distributed"*

From the observed value from Table 20, only temperature that has p - value lower than the alpha of 5% at 95% significance level. $p - value\ of\ confidence\ in\ temperature\ condition = 0{,}024$. In other words, we must reject the null hypothesis in temperature conditions.

Tests of Normality

	Condition	Kolmogorov-Smirnov[a] Statistic	df	Sig.	Shapiro-Wilk 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

Table 20. Shapiro-Wilk and Kolmogorov-Smirnov test on normality

The next test is conducted to investigate further if the population for confidence is normally distributed. As a result, the $p - value\ in\ the\ subjective\ confidence > 0.05$, which means the result of this fails to reject that the data is normally distributed.

Test Statistics[a,b]

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

a. Kruskal Wallis Test

b. Grouping Variable: VAR00001

Table 21. Kruskal-Wallis H test results for mental load

Furthermore, the graph shows that the mental demand required in combination modalities is higher than the single modalities. It is shown that the scale points to a mental load of 6 for the combination modalities. On the other hand, the single modalities have a mental demand of 5,25 points.

In addition, we aim to compare subjective confidence between single and multimodal conditions as depicted in the bar chart from Figure 22. The confidence level for single modalities is measured at an average rate of 4.4, while the confidence level for multimodal conditions is slightly lower, with an average rate of 4.1 on the Likert scale.

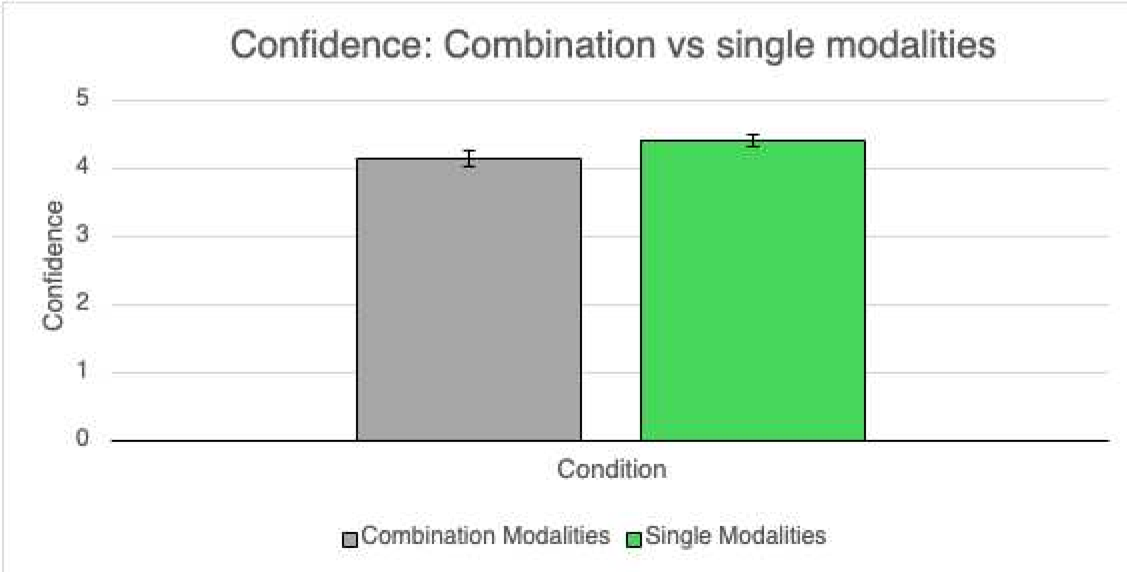

Figure 22. The confidence in answering each LimeSurvey question to compare single modalities and combination modalities study groups.

To show if there is significant difference, Table 22 shows that the p value for the confidence in both combination modalities and single modalities are greater than 0,05. It shows that the data is normally distributed. Therefore, the test fails to reject that the data is normally distributed.

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

Table 22. Shapiro-Wilk and Kolmogrov-Smirnov test result for subjective confidence

The test examines two independent variables: 'multimodal' and 'single modality,' to determine if there is a significant difference between them. However, as indicated in Table 23, the p-value for the two-sided test is 0.225, which is more than 0,05. So, the test does not provide enough evidence to reject the null hypothesis that the data is normally distributed. Therefore, it concludes that there is no significant difference across all conditions.

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

Table 23. Independent samples T-Test for the subjective confidence between combination conditions and single modality conditions

5.9.5. Subjective feedback

The feedback from participants who interacted with different sensory modalities indicates generally positive experiences. Participants found that temperature is a pleasant modality. They enjoyed the actual sensation provided by the installation. They can easily distinguish warm and cold temperatures but reported difficulty determining mid-range to high-range temperatures. The modality was considered intuitive, with some expressing a wish to use both hands for temperature to enhance their experience.

Additionally, vibration was highlighted as a standout modality for its clarity and ease of differentiation. Some participants mentioned that the vibration motor creates a sound, resulting in some of the participants using the sound of the motor rather than the tactile feedback from the vibration motor to find the answer.

Moreover, sound as modality received neutral feedback. Some participants found that the use of tempo was engaging. In contrast, others suggested a need for more clarity about the tempo of the sound. Some participants felt the experience became less engaging over time.

On the other hand, the user also mentions several feedbacks to improve the experience. Users recommended creating a map to show the regions instead of a screen displaying five regions that can be selected. Additionally, most users suggested practical improvements like a time indicator for when the temperature changes will be noticeable and a reduction in the noise produced by the vibration mechanism.

In summary, while each modality was appreciated for its unique experience to the sensory experience, combinations of modalities were generally preferred for their ability to provide clearer and more engaging interactions.

5.9.6. Subjective Preference

In a group with a combination of vibration and temperature, three out of four participants in this group show a preference for vibration, offering clearer and faster feedback. Meanwhile, one out of four participants argued that temperature is better than vibration in conveying the temperature data. These are the example of subjective preference that the user provided:

“Vibration was clearer, didn't really use temperature: mostly sound of the motors”

“The noise is scary, I like the temperature sensing the most, because it has a greater indication.”

"Vibration is more dominant than the temperature."

"When you combine both modalities it gets much clearer. I liked to feel continuity by keeping my hand on the vibration panel while I compared data."

When considering the combination of sound and temperature, three out of four participants found that temperature offers a better understanding of the climate change data. However, one participant argues that sound is easier to understand than temperature. These are the quote from provided subjective preference from this combinations by participants:

"I would say that the temperature makes it clearer than the sound, the sound is just an indicator. "

"The audio is a bit easier to understand what is going on. However, the temperature is also very nice. "

"The temperature helped me more because I was invested in the process of feeling warmth or cold on my hand and the sound was more like background music that immerses you in the experience. "

"Temperature is better in portraying global climate data. "

Finally, in the group of sound and vibration, the feedback showed that most users use vibration as tactile feedback is more stimulating. These are the following feedback from vibration and sound:

"The vibration works better at indicating the differences between the regions."

"I really liked it, but haptic best. "

"Depends on the quality sometimes it is easier to differentiate in audio while sometimes it is easier to differentiate in haptic"

"Temperature indicating air temperature and sea temperature are more straightforward."

5.10. Implication of the results

After analyzing quantitative and qualitative data results, as shown in the previous section, there is no significant difference between all the dependent variables for efficiency, accuracy, mental load, and subjective confidence. Additionally, it shows that the data distribution of all the dependent variables is equally distributed across the conditions. Moreover, there is not much statistical evidence to prove that there is a significant difference between single and multimodal. Therefore, these results show that single and multi-modalities are equally distributed in all the dependent variables.

Additionally, it appears that temperature increased the time users spent answering the question after analyzing the efficiency of all conditions, as shown in Figure 15. The delay of the heat generator to get to the right point impacts the efficiency of a single or combination of temperatures to be less efficient. However, a single or combination of temperatures are shown to have slightly higher accuracy than other modalities. Hence, a single or combination of temperatures is more accurate than other modalities, yet it has the lowest efficiency.

Generally, participants preferred multimodal data physicalization to perceive clearer and more engaging interactions based on subjective feedback. Moreover, the subjective preference provided by participants indicates that vibration offers clearer and faster feedback to convey ordinal data. Participants also preferred to interact with temperature since it is more engaging because the temperature can change from cold to warm.

Chapter 6 - Discussion

6.1. Limitations

Numerous challenges were encountered during the research process in this paper. Initially, we planned to include Electro Muscle Stimulation (EMS) as a primary encoding variable to present haptic feedback. However, due to the limited time to configure the circuit, we attempted to use a random EMS device and configure the circuit independently. Unfortunately, this led to the component breaking, and we were unable to continue applying this modality. The need for more research on using EMS for data physicalization and a lack of schematic examples for circuit construction made it impossible to realize the application of EMS as an encoding variable.

During the process of making the installation, we planned to physicalize all input variables and exclude the visualization. We planned to have a year slider representing the selection of the year and a globe for selecting a region. Instead, we created a year knob using a potentiometer and a 3D-printed globe to display region options. However, a pilot study noticed the messy cables coming out from the 3D-printed globe, making it fragile. Consequently, due to aesthetic considerations, we decided to remove the 3D-printed globe and the year knob from the installation.

Moreover, we planned to install an aluminum plate on top of the Peltier module to decrease the delay in reaching the desired temperature. We chose a 1mm aluminum plate to speed up the heat transfer. As a result, adding the aluminum plate enabled faster heat transfer from the low to mid or high categories. However, the transition from high to mid or high to low took longer because the Peltier module's surface area was much smaller than the plate. This meant the residual heat on the aluminum plate's surface caused greater delays when the temperature needed to decrease. We used a canvas over the Peltier module to address this issue, acting as an insulator and allowing heat to dissipate more quickly.

Additionally, the vibration motor generates noises. Several participants mentioned that they depended more on the sound produced by the vibration motor, making the vibration less reliable as a source of haptic feedback. They found the answers to the questions based on the sonic feedback rather than the intended haptic feedback from the vibration motor.

During the evaluation, participants indicated confusion due to the cursor on the screen being too small and the cursor's color blending in with the background, making it difficult to select a region and a year. This issue disrupts their experience with data physicalization. Observations suggest that this limitation adversely affected the efficiency across all conditions.

Lastly, we planned to have 36 participants evaluate the single and combined modalities across six conditions, which would mean 6 participants per condition. However, we could only recruit 24 participants for the user evaluation due to time constraints and other factors. The shortfall in participants was primarily due to a lack of responses. Despite distributing a registration form via social media and email, we gathered only 24 participants to evaluate our installation.

6.2. Recommendation

In the user study participants give feedback in order to enhance the experience of using our installation. Participants gave several recommendations to improve the installation.

Firstly, most participants recommended adding a waiting time indicator on the screen for the temperature modality and its combinations. This indicator would signal when the temperature reaches the intended level, addressing the confusion caused by the 6-second delay in temperature adjustment. An alternative solution, suggested by a participant from the combination of vibration and temperature conditions, involves synchronizing a 6-second delay with the vibration. Hence, the vibration would activate or start vibrating only once the temperature has reached the desired temperature.

Secondly, some participants mentioned the noise cast by the vibration motors. One suggestion is to install acoustic panels between the motors to minimize vibration noise. Another recommendation is for users to wear noise-canceling headphones, which would help them not to be disturbed by the noise.

In addition, one participant mentioned that the screen's design was too simple and suggested enhancing the GUI to make the visuals more aesthetically pleasing. An improvement to the GUI's design and the visualization was recommended to address this issue.

6.3. Future work

There is still a lot of room in improving the installation. As mentioned, this research aimed to present data through physical variables, shifting away from traditional visualizations. One enhancement could be the addition of a globe, enabling users to select a region by pressing a button on the corresponding area. This approach would improve data comprehension by allowing users to visually and physically locate the region on the globe. Furthermore, making the year slider a physical component could significantly enrich the user interaction experience. Hence, physicalizing all input indicators could greatly enhance the overall user experience.

For future work, exploring more modalities, such as Electro Muscle Stimulation (EMS), could provide valuable insights into their impact on data perception and user experience with a larger observation sample. Thus, evaluating the effects of various sensory modalities could be a beneficial area of research.

Chapter 7 - Conclusion

This research paper explores multimodal data physicalization for climate change communication, focusing on haptic and auditory modalities. It aims to address the following research question:

RQ: *How do different combinations of modalities: temperature and sound, vibration and temperature, and each modality separately, compare in data perception and user experience of a data physicalization conveying climate change data?*

The results from user evaluations indicate no significant difference in data perception across all conditions. Efficiency, accuracy, mental load, and subjective confidence were similarly distributed among all modality combinations. Additionally, comparisons between single modalities and their combinations showed no significant differences in the perception of ordinal climate change data. Subjective preferences suggest that participants found haptic variables more stimulating and engaging, particularly in combined modalities. The haptic variables include temperature, vibration, and both combined as the modalities.

In conclusion, there is no significant difference in data perception among the combinations of modalities: temperature and sound, vibration and temperature, and each modality separately. However, the use of multimodal combinations: temperature and sound, vibration and temperature, and vibration and sound, appears to enhance the overall user experience.

If there is additional time for improvement, it would be beneficial to conduct evaluations with 36 participants or sample size that is bigger than 24 to determine if there are significant differences across all conditions.

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Appendix A: Information Letter and Consent Form

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

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 B: Dataset

Land Precipitation (mm/month)					
YEAR	ANTARTICA	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

Air Temperature (ºC)					
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

Sea Temperature (ºC)					
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

Appendix C: Ordinal Dataset

Land Precipitation (mm/month)					
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

Sea Temperature (ºC)					
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 (ºC)					
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

Appendix D: Arduino Code and Python Code

Indicator Arduino Code

```
#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 Code

```
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 Code

```
//#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
    } 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

    }
    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
    }
  }
}
```

Python Code

```python
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: Preliminary knowledge form and Familiarization Tasks.

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?