# *Assessment Report*

# *Understanding Neuroscience of Touch*

*For the period*

August 2025 to November 2025

***by***


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# 1 Introduction to Neurohaptics Research [1]

## 1.1 Understanding the Foundations: Haptics and Neuroscience

Haptics, the study of touch, is integral to our perception of the world. Our biological sensors, including eyes, ears, and skin, play unique roles in forming our cognitive understanding of the environment. Of particular interest is the haptic modality, which involves neural networks dispersed throughout the body, particularly the somatosensory system. The skin, covering approximately 1.8 $m^2$ and weighing 5 kg in adults, serves as a vital interface for discriminative and affective functions. Haptic perception, encompassing the senses of touch, pressure, temperature, pain, and pleasure, holds paramount importance in daily activities, facilitating object manipulation, shape discrimination, and environmental interaction.

Neuroscience provides the framework for comprehending the neurobiological underpinnings of touch. More than half of the human brain is devoted to processing sensory experiences, with touch playing a pivotal role in communication with the physical world. Traditional research methods relying on self-reporting or behavioral observation have limitations, prompting the exploration of neurophysiological methods such as functional magnetic resonance imaging (fMRI) and EEG.

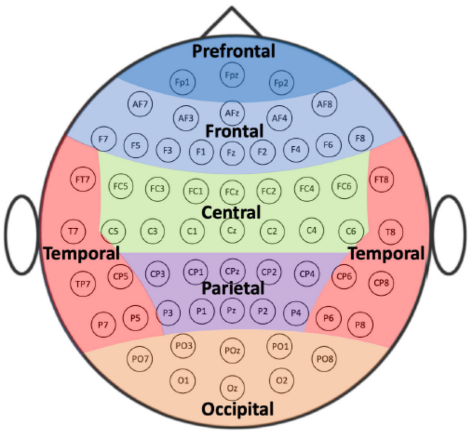
## 1.2 Understanding Neuro-Haptics

At its core, neuro-haptics investigates the neural mechanisms that govern our sense of touch and aims to apply this understanding to the development of haptic technologies. The human sense of touch is a complex interplay of sensory receptors, neural pathways, and cognitive processes. Neuro-haptic researchers delve into the physiology of touch, studying how our nervous system processes tactile information and translates it into the rich tapestry of sensations we experience.

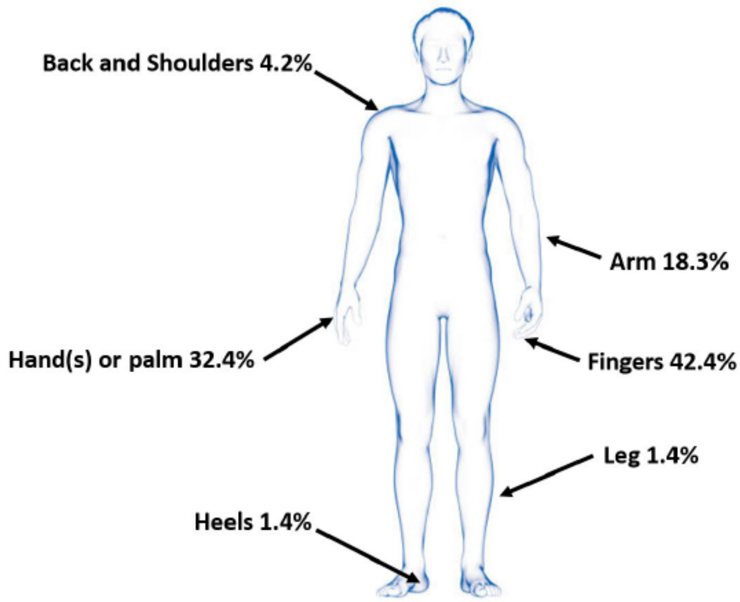
One key aspect of neuro-haptics is the exploration of somatosensation, which encompasses the various sensory modalities related to touch, pressure, temperature, and proprioception. Researchers seek to unravel the mysteries of how the brain interprets signals from the skin and other sensory organs, allowing us to interact with the world in a nuanced and sophisticated manner.

## 2 EEG as a Gateway to Neurohaptic Insights

Unlike fMRI, EEG offers a cost-effective alternative for recording cortical neural activation. Its advantages include a lack of dependence on a shielded room, participant mobility, and high temporal resolution, allowing real-time analysis of neural mechanisms underlying touch.




(a) Electrodes locations and brain cortical regions




(b) Body parts involved in neurohaptics experiments

### 2.1 EEG-Based Analytical Methods:

EEG signals are often contaminated with artifacts, which can be either physiological or non-physiological. Physiological artifacts include those originating from body parts other than the brain, such as eye movements, muscle activities, and cardiac potentials. Non-physiological artifacts, on the other hand, arise from external sources like electronic devices and power lines.

To enhance the quality of EEG signals, researchers employ various analytical methods for artifact removal. Common approaches include simple filtering using notch filters to eliminate power line interference and more complex methods like event-related potentials (ERP), somatosensory evoked potentials (SEP), steady-state somatosensory evoked potential (SSSEP), and power spectral density (PSD). Filtering methods alone, such as bandpass, low pass, or high pass, may not be sufficient for eliminating different types of artifacts.

Intra-regional analysis involves studying EEG features within specific regions of the cortex. This includes ERP, which represents microvolt voltages generated in response to specific stimuli and can be divided into exogenous and indigenous components. SEP, on the other hand, is generated in response to touch stimuli, with early components reflecting physical characteristics and later components indicating higher cognitive processing. SSSEP involves

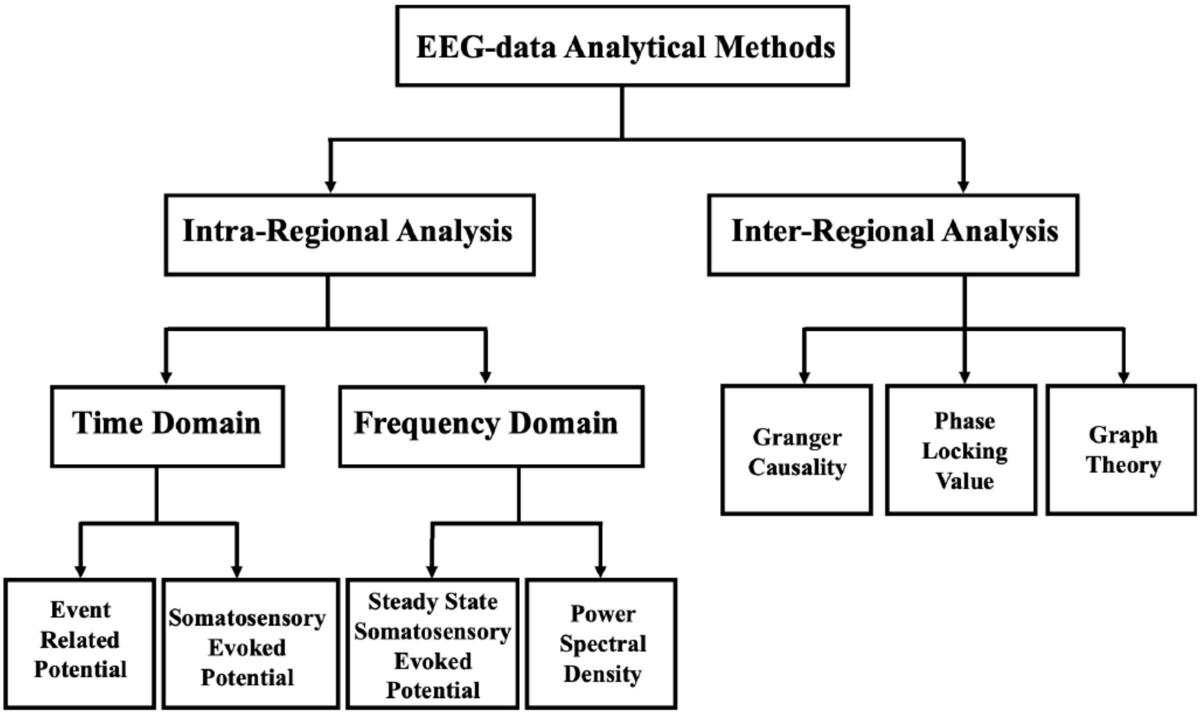



Figure 2: Taxonomy of EEG data analysis methods in Neurohaptics.

applying vibrations to the skin, and PSD focuses on analyzing the average power of EEG signals in specific frequency ranges.

### 2.2 EEG-Based Neurohaptics Studies:

More than 70 neurohaptics studies have utilized EEG to investigate neural responses related to touch, with a focus on different body parts, such as hands, palms, and fingers. Around 55% of these studies examined passive touch, while 45% investigated active touch. The studies were categorized into various themes, including emotions and touch, observed touch, haptic memory, discriminative touch, and tactile perception with age.

1. Emotions and Touch: Affective touch explores how haptic stimuli can elicit emotional responses. Studies in this category used fabric-based devices and EEG data analysis to investigate neural responses, revealing alpha rhythm suppression in the contralateral somatosensory cortex as a prominent feature associated with the endogenous aspect of tactile processing.

2. Observed Touch: Observing touch can activate the primary somatosensory cortex, indicating the role of mirror neurons. Studies in this category explored alpha rhythm suppression as a key EEG feature during observed touch, with implications for empathic interpersonal sharing of haptic experiences.

3. Haptic Memory: Haptic memory involves the retrieval of information related to touch stimuli. EEG studies in this category revealed theta power oscillations in the central and parietal cortex, indicating a correlation with the complexity of haptic stimuli.

4. Discriminative Touch: Discriminative touch is crucial for perceiving pressure, heat, texture, and vibration. EEG studies in this area focused on features such as P300 peaks and power spectral density, revealing correlations between neural activations and the discrimination of surfaces with varying roughness.

In summary, EEG-based analytical methods play a crucial role in enhancing signal quality by addressing artifacts, while EEG-based neurohaptics studies provide valuable insights into the neural mechanisms underlying various aspects of touch and haptic perception. These studies contribute to our understanding of how the brain processes and responds to tactile stimuli, with potential implications for applications in neurohaptic technologies and rehabilitation.

# 3 Literature Review based on previous Research Work

## 3.1 EEG-based Machine Learning Models to Evaluate Haptic Delay: Should We Label Data Based on Self-Reporting or Physical Stimulation? [2]

In the realm of human-computer interaction, haptic interfaces play a pivotal role in providing realistic tactile feedback. The central question addressed is whether labelling EEG data based on self-reporting or actual physical stimulation yields more accurate insights into haptic experiences.

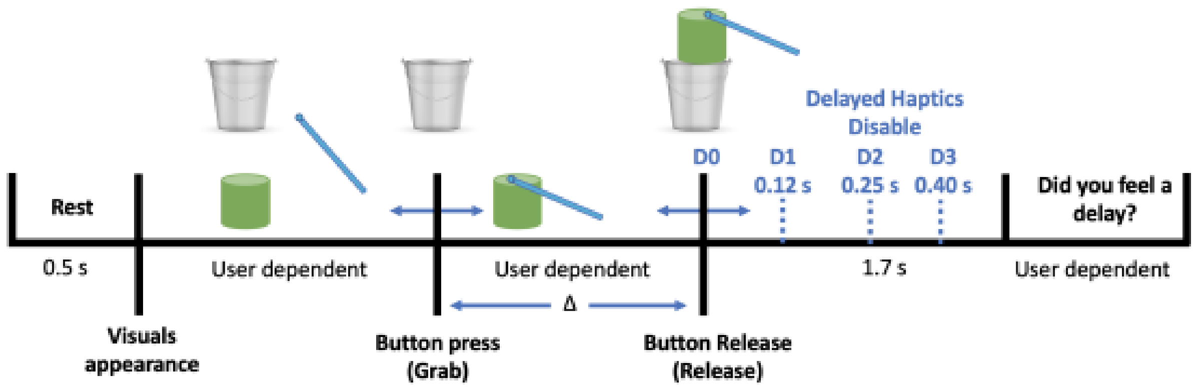
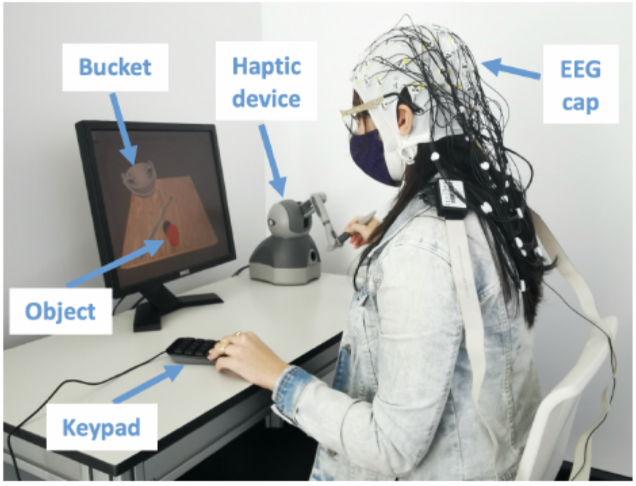
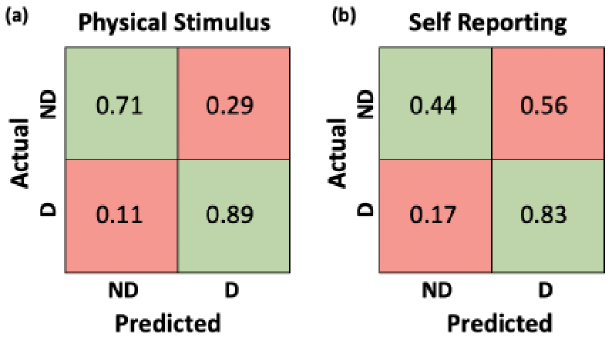



Figure 3: Enter Caption

The experimental results presented in the paper suggest that models trained with labels derived from actual physical stimuli outperform those trained on self-reporting labels. The 2D EEG-CNN outperforms the transformer model. However, the paper acknowledges the need for further research to generalize these findings to various haptic experiences. It emphasizes the ongoing value of self-reported feedback in capturing subjective aspects of user experience, hinting at the potential for a hybrid approach that combines objective neurocognitive measures with subjective insights. The discussion encourages the continued exploration of EEG-based models for haptic assessment, highlighting their potential for unveiling nuanced insights into subtle haptic experiences that might be overlooked by traditional evaluation methods. This paper sets the stage for future research to refine the assessment of haptic interfaces through innovative EEG-based approaches.




(a) The experimental setup




(b) Average of normalized confusion matrices over 10 folds for the CNN model based on Physical stimulus and Self-reporting labeling.

### 3.2 Active touch classification using EEG signals [3]

The study's methodology engages four healthy, right-handed participants in actively touching different natural textures, ranging from smooth to rough and a water surface and the EEG signals were recorded. The classification employs four algorithms - Linear Discriminant Analysis, Support Vector Machines, k-Nearest Neighbor, and Random Forests - revealing intriguing insights into the linear characteristics of the classification problem.

The findings showcase classification accuracy ranging from 64% to 76%, emphasizing the efficacy of EEG-based approaches in discerning brain states during haptic stimuli. The synergistic use of time and spectral features outperforms relying solely on spectral features, highlighting the nuanced nature of the neural response during active touch. Linear algorithms, notably LDA and linear SVM, demonstrate superior performance, suggesting the linear nature of the underlying neural processes.

### 3.3 Recognition of Tactile-related EEG Signals Generated by Self-touch [4]

The paper analyzed changes in the brain caused by movement according to active touch and changes in the brain according to tactile sensation were compared and analyzed. Six participants (right-handed, aged 26±6 years) underwent touch and movement tasks. EEG signals were recorded using 64 electrodes and analyzed using time-frequency and statistical methods.

Significant differences in power changes were observed in alpha, beta, gamma, and high-gamma regions. Also, spatial differences were identified in the sensory-motor area of the brain.

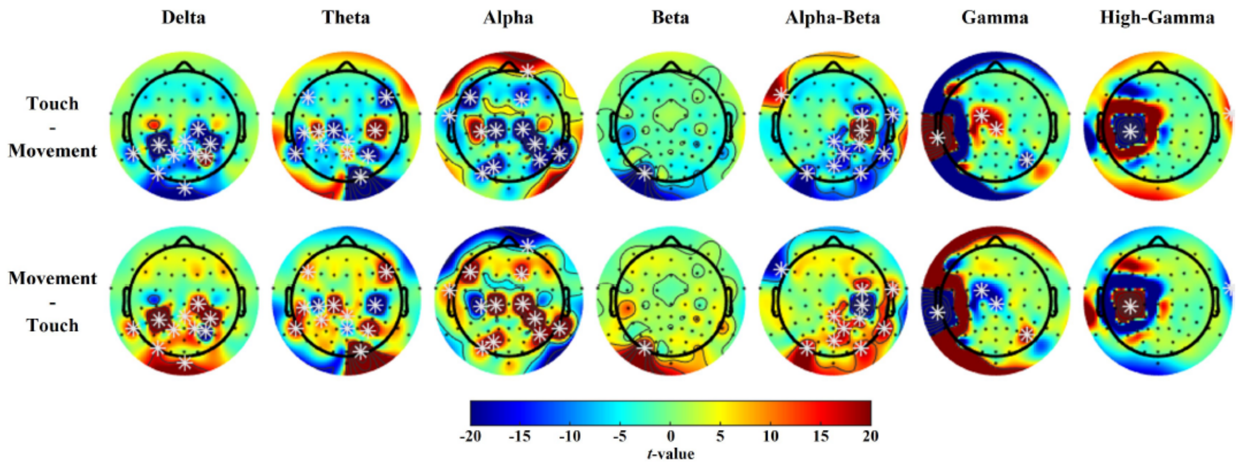
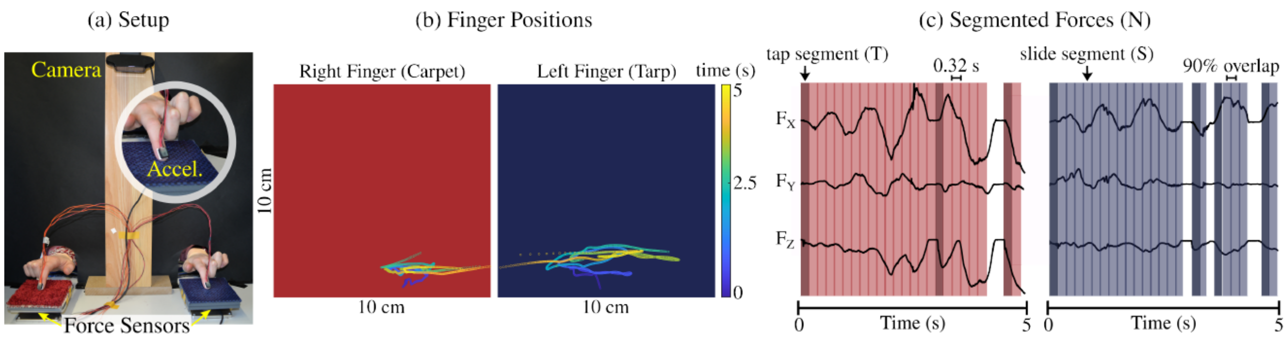



Figure 5: Differences in spectral power between touch and movement tasks. The statistical results represent t-values in each frequency band for differences between touch and movement tasks using a paired-samples t-test.

### 3.4 Learning to Feel Textures: Predicting Perceptual Similarities from Unconstrained Finger-Surface Interactions [5]

The primary objective of this paper is to unravel the intricate relationship between tactile information garnered from finger-surface interactions and the human perception of surface similarity during active touch. Departing from traditional approaches, the authors introduce a novel methodology. Instead of relying on general surface descriptors, they delve into the specifics of unconstrained finger-surface interactions. The proposed method converts these interactions into distributions of features, subsequently calculating distances between these feature distributions based on human-perceived similarity.




The study employs machine learning models to predict perceptual similarity from these feature distributions. Impressively, the method achieves a maximum Spearman's correlation of 0.7, indicating its efficacy in capturing the nuanced nature of individual participants' judgments. Noteworthy is the finding that different participants exhibit variations in how they weigh interaction features when assessing surface similarity. The implications extend beyond theoretical understanding, holding promise for practical applications in haptic surface assessment, robotic tactile perception, and the realm of haptic rendering.

While the study provides valuable insights, challenges persist. Notably, there are variations in prediction accuracy across participants, suggesting the influence of individual differences in the weighting of features during texture perception. Furthermore, the comparison of simple models, like affine maps, performing comparably to more complex neural networks, prompts considerations about the balance between model simplicity and complexity. This suggests that the method's limitations might not lie in the choice of model type.

## 4 Problem Statement

Existing research highlights the significance of haptics in shaping cognitive understanding, particularly the neurobiological foundations of touch. Current methodologies, however, fall short in capturing the intricate nuances of tactile experiences due to the predominant reliance on behavioural observation and self-reporting. To address this gap, we propose a novel approach that is different from conventional haptic research paradigms. Instead of using established methods like EEG and fMRI solely for classification, our focus is on exploring their potential for unveiling unknown classes and patterns in touch perception. Our proposed study involves participants actively engaging in touch experiences, exploring various materials, and assessing them. The collected data, including EEG signals and Likert scale ratings (taken from the user's perception), will be analyzed to understand the underlying neural mechanisms associated with the perception of material attributes.

Inspired by the need to delve deeper into the neurohaptic landscape, this deviation from conventional approaches aims to unravel novel insights into the interplay between the brain and touch experiences. The research specifically investigates the impact of different textures on the brain, employing EEG analysis to cluster objects and include unknown classes. The study assesses the roughness of objects through tactile exploration, incorporating Likert scale ratings for similarity. The objective is to understand the relation between the roughness and hardness of objects, exploring if they cause similar effects and if their EEG responses are interconnected. Additionally, a future aspect of the research aims to determine the dependency of hardness perception on the sense of touch or hearing, examining the relationship between perception and these senses.

The motivation for this research stems from a gap identified in existing literature, where force analysis studies different textures based on mechanical factors but lacks EEG analysis. The classification of objects based on EEG data analysis is considered a crucial and timely pursuit, but only limiting the analysis to classification does not help introduce new objects in the same study. We, therefore, aim to perform clustering on and display inter-class as well as intra-class variation, which would also allow new materials to be introduced in our study by comparing them with the existing clusters. This foundational research can have profound applications, especially in the context of the developing metaverse and robotics.

# 5 Experimental Design

During the experiment design process, some fundamental questions had to be answered to find the best procedure that met the requirements of the experiment. Some of the technical aspects which we worked on are listed below:

## 5.1 Surface Interaction

1. **Stylus vs Finger:** Initially, the experiment used a stylus to scratch the surface. However, since a stylus didn't generate as robust an EEG response as the tactile sensation of actual touch, we opted to transition from the stylus to using the hand.

2. **Movement on the surface:** The initial design proposed moving the stylus in a top-to-bottom and right-to-left direction. However, after thorough discussions, it was determined that moving the stylus in a circular motion was more optimal. This approach allows us to gather information about the stimulus's texture from all directions and minimises the loss of information.

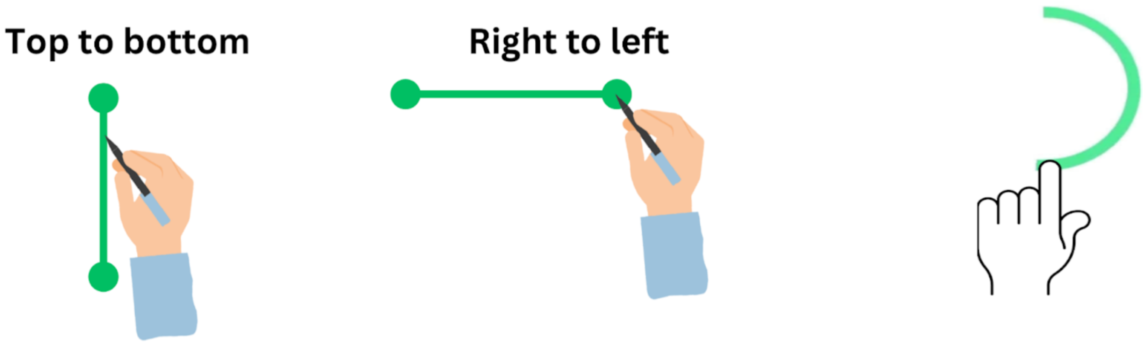



Figure 6: Surface Exploration

## 5.2 Procedure

1. **Roughness and Hardness:** In the initial phase of the experiment design, the objective was to evaluate the surface's roughness and hardness. To address both aspects, we devised the initial experimental procedure, which involved utilizing an audio component to examine the correlation between hardness and auditory signals.

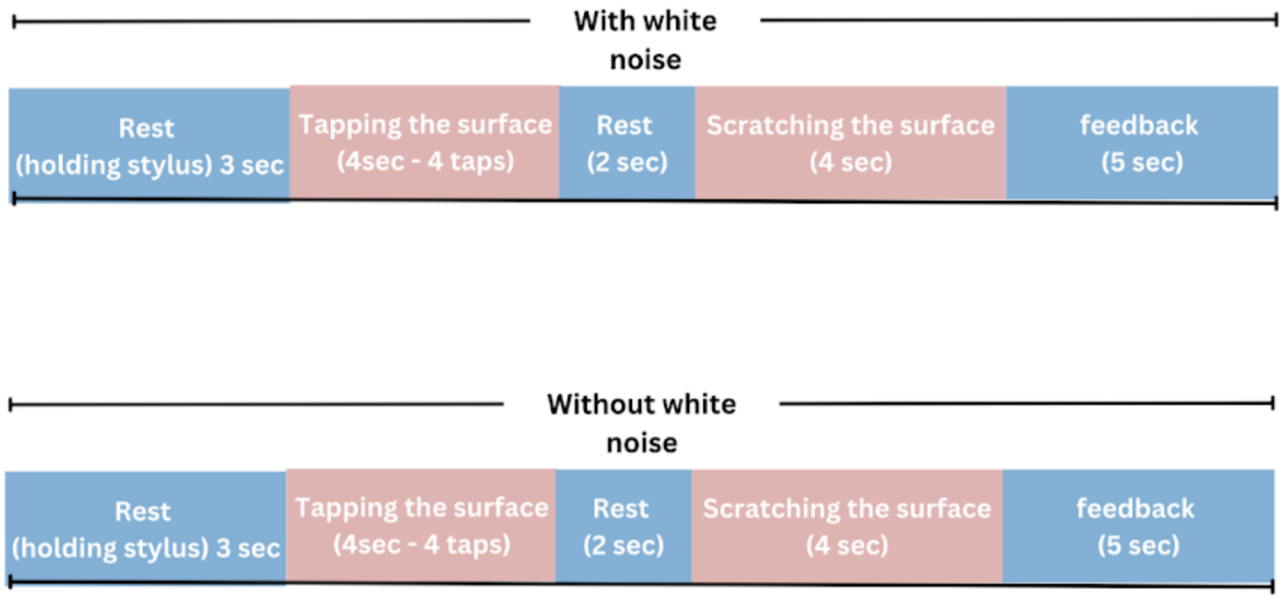



Figure 7: Preliminary Trial Design

However, the aforementioned procedure proved to be excessively time-consuming and impractical. Consequently, we needed to adopt a more efficient approach to reduce the duration of the experiment. To achieve this, certain components related to hardness analysis and the audio element were temporarily excluded. We plan to revisit the analysis of hardness and sound as an extension of our current research in a later stage.

2. **Roughness Analysis:** Addressing the gap highlighted in the problem statement, the existing research lacks a clustering analysis of the roughness similarity among various objects. Consequently, we designed an experiment focusing on roughness analysis due to its practicality and manageable duration, making it a more feasible choice for investigation.

### 5.3 Eye movement minimisation cues

To mitigate the impact of unnecessary eye movements on EEG signals, we incorporate fixation points at the onset of each trial. This serves the dual purpose of establishing a baseline and reducing noise in the EEG recording. Additionally, to ensure that the movements in various recordings are similar, we created a consistent pattern to make the trials more standardised. This ensures that the data relies more on textures rather than being influenced by other factors.

### 5.4 Feedback and responses

1. **Similarity Score:** In gathering the feedback for similarity ratings of objects from the participants, we employed a Likert scale ranging from 1 to 9, where 1 indicated the

least similarity, and 9 denoted the highest level of similarity.

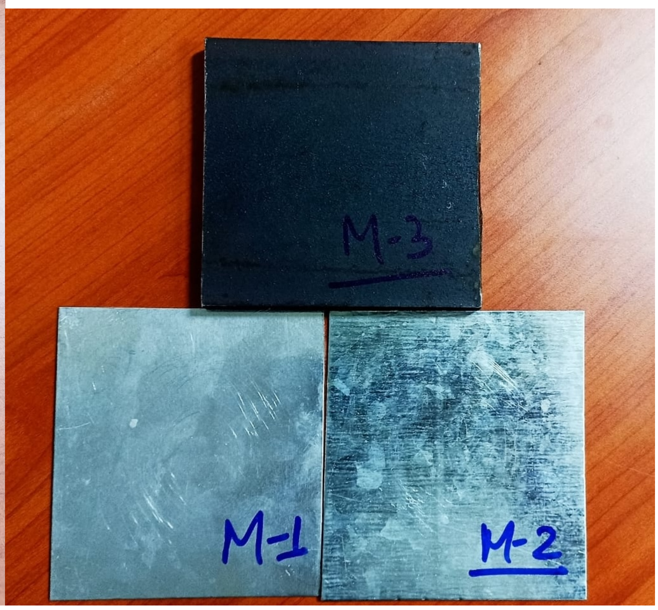
2. **Response:** To minimise EEG interference caused by unnecessary hand movements, we recorded audio feedback for all participant responses, storing their ratings of object similarity.

### 5.5 Stimuli Selection and Procurement

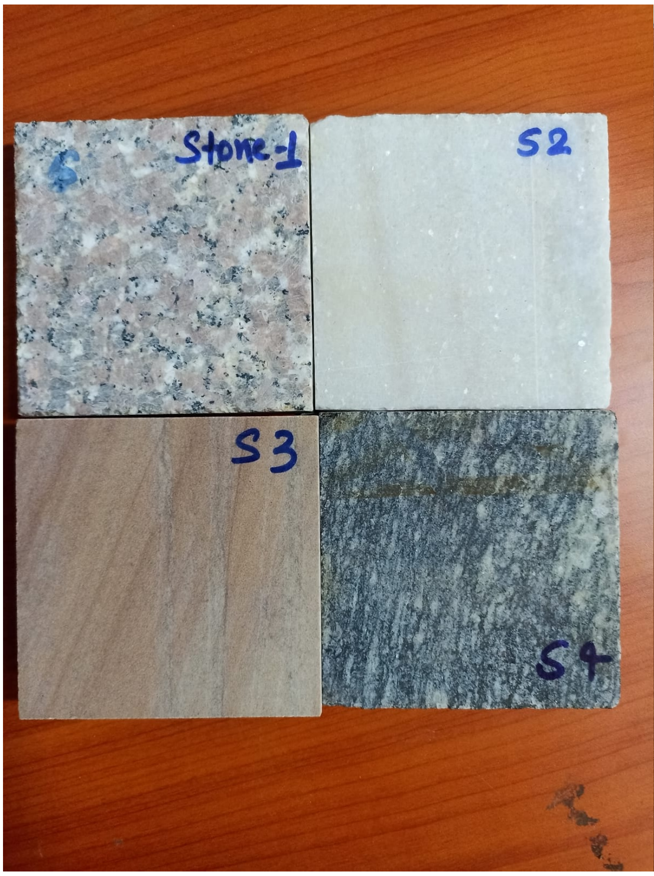
1. **Material Choice:** We chose 15 surfaces to serve as stimuli, encompassing four categories: wood (4 types), stones (4 types), glass (4 types), and metal (3 types). The rationale behind selecting these categories is the diverse material properties within each, providing a haptically varied stimulus set.

2. **Sourcing:** To obtain the surfaces for our stimuli, we engaged in an ongoing process of identifying vendors and making frequent visits to ensure the acquisition of high-quality materials aligned with the experiment's evolving demands.

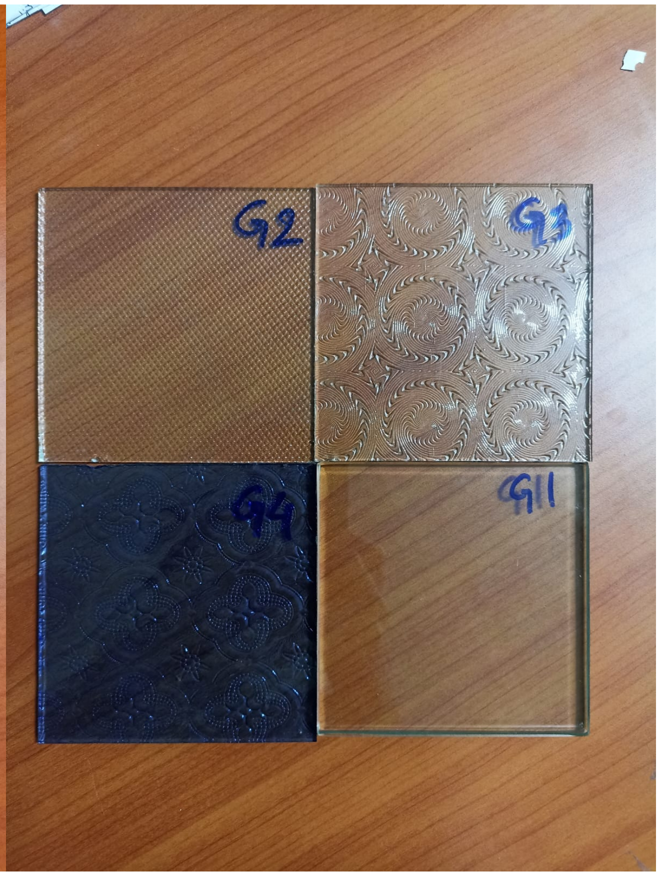
(a) Wood



(b) Metal




(a) Marble




(b) Glass

### 5.6 Eliminating Bias and Randomization

1. **Bias Elimination:** Participants are kept unaware of the various types of objects they will encounter to eliminate any potential bias. Additionally, surfaces are concealed during the experiment to prevent unintended bias stemming from visual stimulation.

2. **Randomisation:** We employed software to generate random pairs, minimising unintentional bias. Furthermore, we ensure that each object is presented both under the right and left hands, providing a comprehensive understanding of EEG signals generated while feeling the textures.

### 5.7 Integration with External Devices

The Emotiv EPOC X device was utilised for capturing the EEG recordings. Several training sessions were conducted to familiarise ourselves with the device's usage, as detailed in a later section of this document.

### 5.8 Code Component

For placing markers on the recording and integrating all components to assemble the complete experiment, we employed PsychoPy software. This choice was made due to the multitude of features it provides, essential for encompassing all aspects of the recording. Further specifics regarding the actual setup are elaborated upon later in the document.

## 6 Final Experiment Design

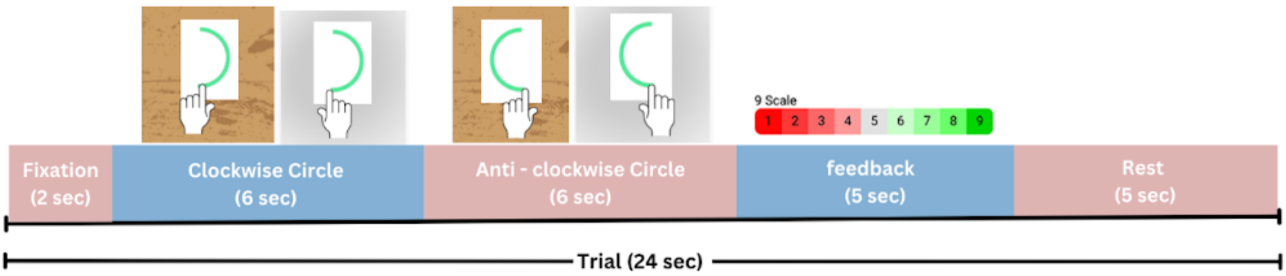



Figure 10: Final Experiment Design

## 7 Data Collection

### 7.1 Integration with the software and Hardware - Working with the Emotiv EPOC X headset


Figure 11: Emotiv EPOC X Headset

EMOTIV EPOC X 14 channel mobile EEG is designed for scalable and contextual human brain research and advanced brain-computer interface applications and provides access to professional-grade brain data with a quick and easy-to-use design.

### 7.2 Specifications of the EPOC headset:

1. It has 14 channels: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4
2. 2 references: CMS/DRL references at P3/P4; left/right mastoid process alternative
3. Sensor material: Saline-soaked felt pads

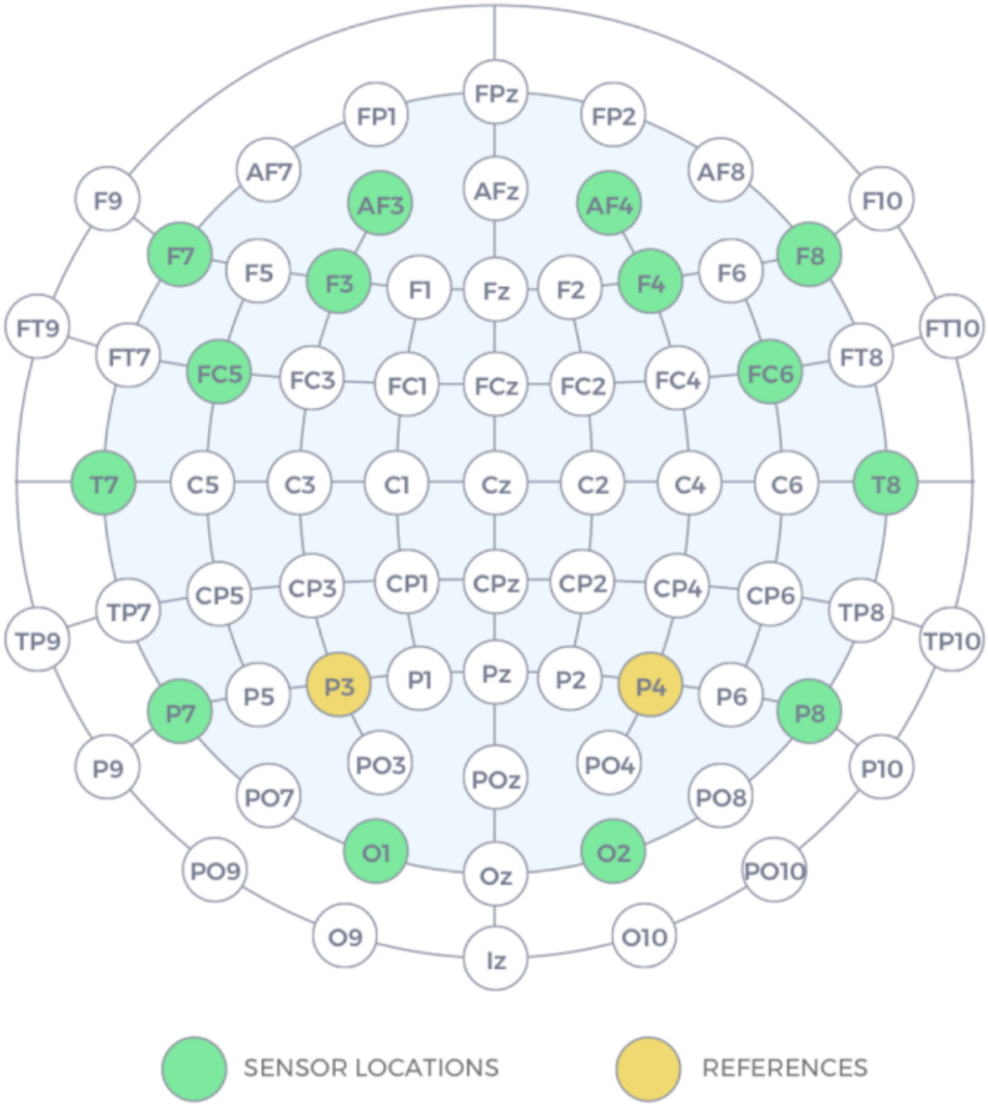



Figure 12: Sensor Locations

### 7.3 Connectivity

1. Wireless: Bluetooth Low Energy
2. Proprietary USB receiver: 2.4GHz band

3. USB: to change headset settings

### 7.4 EEG signals

1. Sampling method: Sequential sampling, single ADC
2. Sampling rate: 2048 internal downsampled to 128 SPS or 256 SPS (user configured).
3. Resolution: 14 bits with 1 LSB = 0.51V (16 bit ADC, 2 bits instrumental noise floor discarded), or 16 bits (user configured)
4. Bandwidth: 0.16 – 43Hz
5. Resolution: 16 bits


Figure 13: Headset Components

We learned how to use the EPOC X headset and devised a step-by-step procedure for collecting data.

## 7.5 Steps to operate the EPOC X headset and collect data from a participant

### 7.5.1 Wet the Felt Pads:

1. Use the saline solution from the headset kit.
2. Apply it all over the sensor felt pads, ensuring they feel wet to the touch.
3. Alternatively, submerge the felt pads in a glass of saline solution.

### 7.5.2 Connecting the Headset:

1. Plug the USB dongle into the computer.
2. Switch on the headset (On: left position, Off: right position)
3. Once paired, the light indicating the dongle pairing turns on.
4. Ensure the headset is fully charged before a long recording.

### 7.5.3 Fitting the Headset:

1. Slide the headset down over the ears, starting from the top of the head.
2. Position the rubber comfort pads on the large bone behind the ears.
3. Tilt the headset until the front sensors are three fingers above the eyebrows.
4. Ensure the two sensors at the back are not twisted. Push them down if needed.

### 7.5.4 Handling Sensors Underneath Hair:

1. For long hair: We tie it in a high half ponytail for long hair to keep it out of the way.
2. Work each sensor underneath the hair, sweeping any hair away from the sensors.

### 7.5.5 Checking Signal Quality Map:

1. Examine the signal quality map in Emotiv Pro. Ensure reference sensors have a stable green signal.
2. Adjust other sensors by adding saline solution and allowing time to settle.

### 7.5.6 Inspecting Raw EEG Data:

1. Set channel spacing to 80 microvolts in the raw EEG tab of Emotiv Pro.
2. Observe the clean signal, ensuring brainwaves do not overlap.

### 7.5.7 Checking Wireless Connection:

1. In Emotiv Pro, click on the data packets tab.
2. Ensure the sawtooth pattern is smooth with no vertical red lines, indicating no packet loss.

### 7.5.8 Troubleshooting Wireless Issues:

1. If packets are lost, move away from electronic devices or use a USB extension cable.

### 7.5.9 Recording EEG Data:

1. Once all checks are successful, the device is ready to record high-quality EEG data.

## 7.6 PsychoPy (Software to implement the experiment design):

PsychoPy is an open-source software package for creating experiments in psychology and neuroscience. It provides a versatile platform for designing and conducting a wide range of experiments, including devices like Emotiv EEG (electroencephalogram) headset. By combining the capabilities of PsychoPy and the Emotiv headset, researchers develop sophisticated experiments that involve both behavioral and physiological measures. The integration allows for a comprehensive understanding of cognitive and emotional processes during various tasks and conditions. Here's a brief overview of how PsychoPy is used with Emotiv to design our experimental procedure:

1. PsychoPy Setup: In experiment settings, we specify the parameters such as screen resolution, background color, and other general settings.
2. Stimulus Design: We design our experiment stimuli using PsychoPy's Builder interface. This included presenting visual stimuli on the screen. Implement conditions, trials, and response collection as per our experimental design.
3. Integration with Emotiv: Used PsychoPy's programming capabilities to integrate Emotiv functionality. Importing the necessary libraries from the Emotiv SDK to communicate with the EEG headset. Set up the Emotiv headset to record EEG data during the experiment.
4. Data Recording: We implement markers using PsychoPy to mark the relevant sections of the recording from the Emotiv headset during the experiment.
5. Feedback and Monitoring: Our experiment involves real-time feedback of user based on the similarity between the objects, so PsychoPy is programmed to take the feedback as input on a likert scale.

6. Experiment Execution: On running the experiment within the PsychoPy environment, the software will control the presentation of stimuli while simultaneously recording EEG data from the Emotiv headset.

### 7.7 Experiment design on PsychoPy:

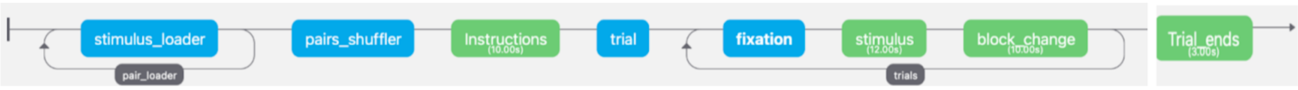
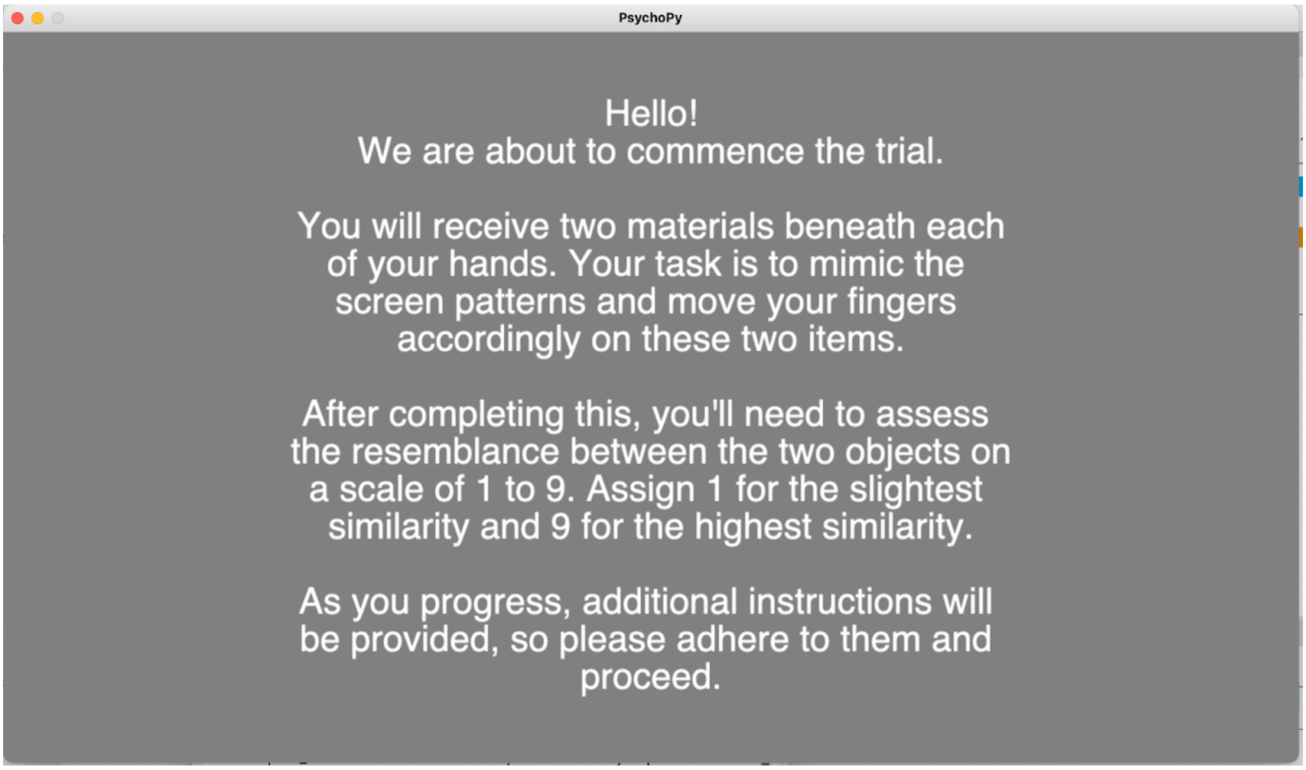



Figure 14: PsychoPy timeline

1. Stimulus Loader and pairs_shuffler: Used for loading the 105 different pairs in the experiment, and randomise their placement on the left and the right-hand side.

2. Instructions: These are the initial instructions provided to participants before commencing the experiment, explaining its nature and guiding them on what to do.




### 7.8 Experiment Trial:

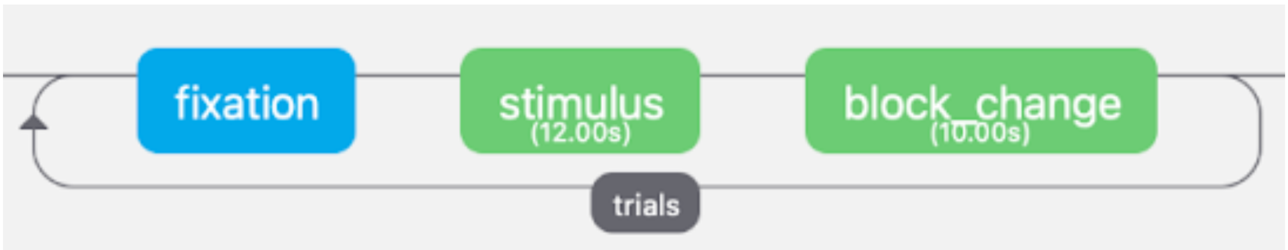


Figure 15: PsychoPy Trial

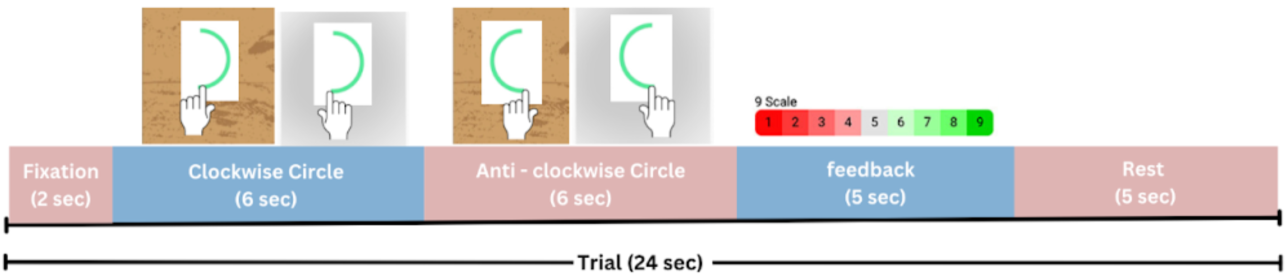


Figure 16: Experiment Trial

**Stimulus for clockwise and anti-clockwise movement:** Video stimuli are provided for moving the finger on the surface.

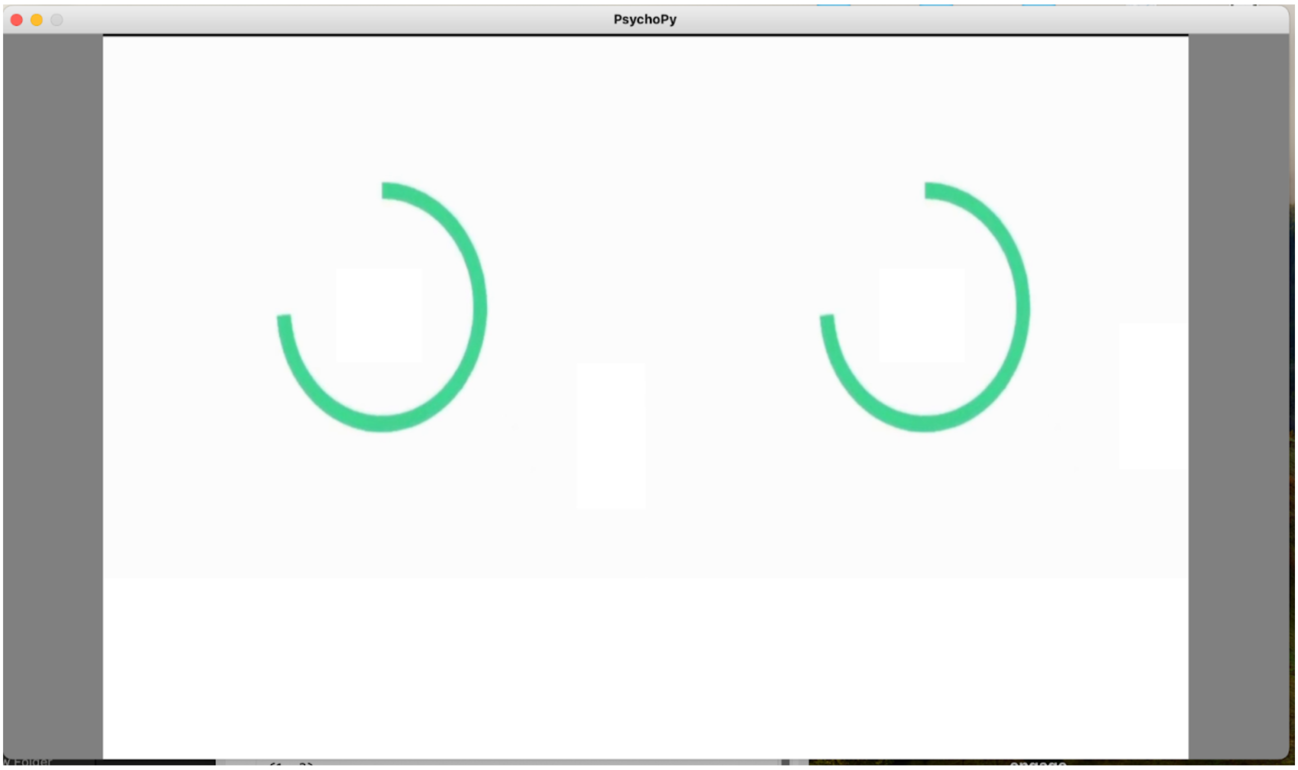



Figure 17: Clockwise Stimulus

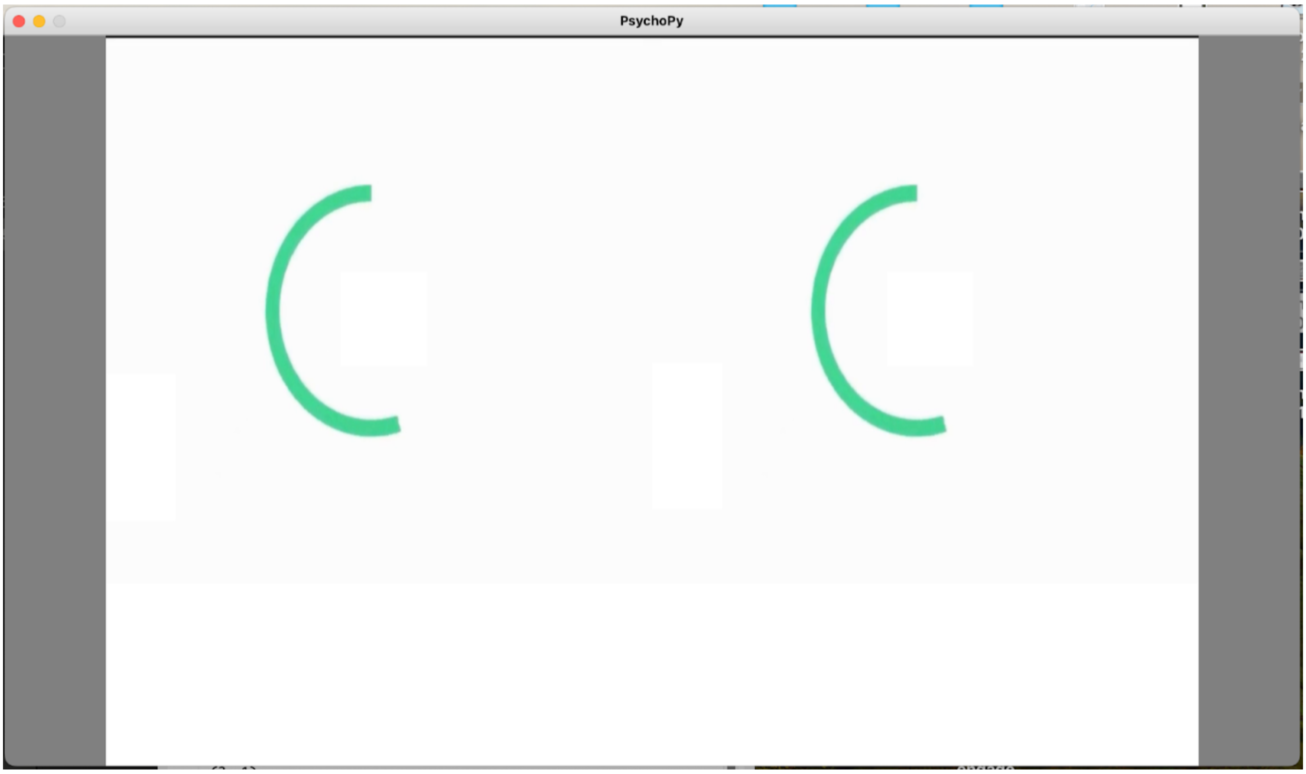



Figure 18: Anticlockwise Stimulus

**Feedback and Response:** for recording the response, we take in the audio recording from the participant as stated above in the experimental design.

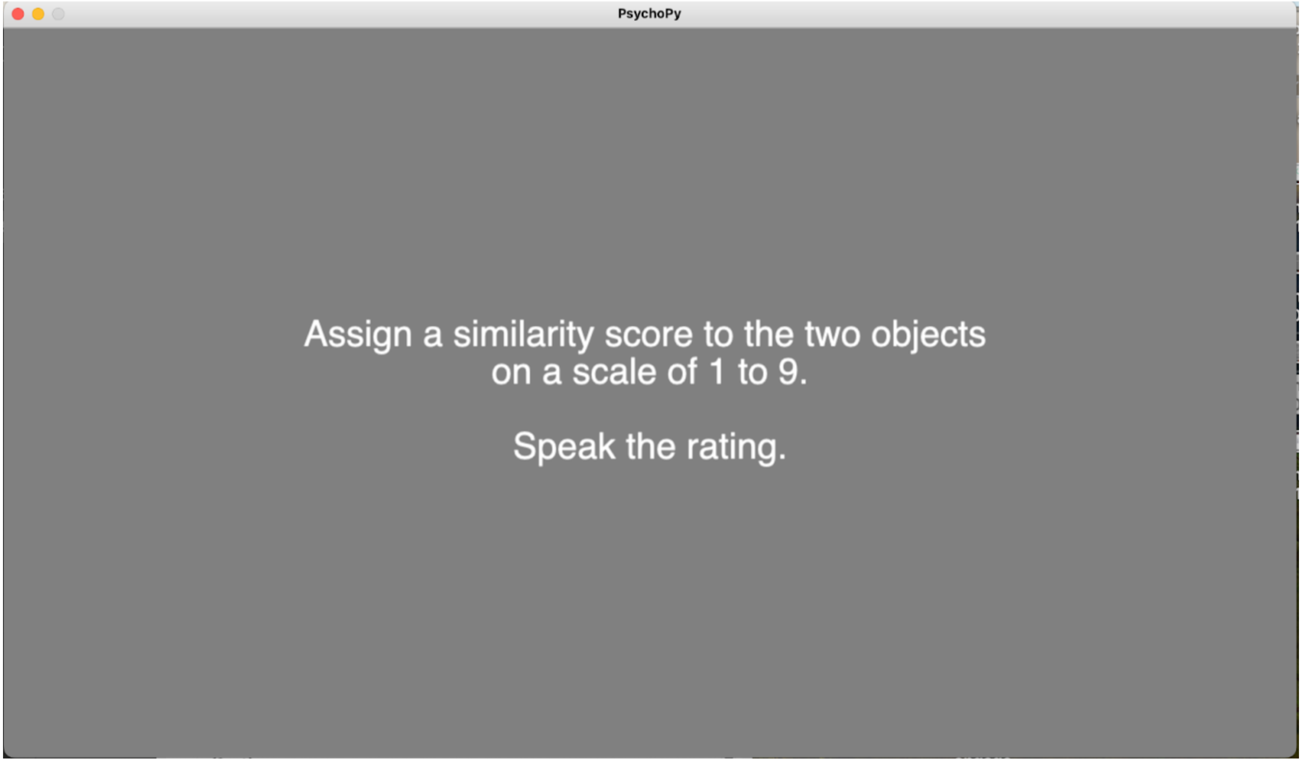



Figure 19: Feedback Screen

In summary, our study addresses a critical knowledge gap in the neurobiological effects of touch through the introduction of an innovative haptic research approach. We use EEG signals and Likert scale ratings not just to classify but to find new patterns in how we perceive touch. Instead of following the usual methods, we look closely at how different textures affect the brain. We use clustering analysis for objects and include new materials in our study to understand touch better.

Foundational in nature, this research holds relevance for applications in the metaverse and robotics, offering insights to enhance user experiences and deepen our comprehension of the brain's involvement in tactile sensations. In conclusion, our work aims to contribute significantly to a more thorough understanding of haptics, extending to both scientific exploration and technological advancement.

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