Remote Emotional Interactions via AI-Enhanced Brain-to-Body Neurophysiological Interface

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Abstract: The rapid growth of Artificial Intelligence (AI) has led to the emergence of Human-AI Interaction. This area explores how humans and AI systems can effectively collaborate and communicate. Recent studies have shown that using traditional approaches might not be adequate to capture issues arising from the combination of methods of these disciplines. A recent approach emerging in human-computer interaction (HCI), the socioenactive approach, represents a new possibility for capturing aspects in the confluence of AI and HCI due to its focus on the social-physical-digital coupling. In socioenactivity studies, the brain, body, senses, perception, cognition, sensorimotor, and emotions in interactions with people, physical objects, and computational systems. This study investigates and develops a socioenactive system empowered with AI that is designed to foster and enhance socio-emotional interactions between participants who are connected remotely. Our solution has the potential to significantly impact the field of Human-AI Interaction, by providing a deeper understanding of the interaction and coupling between human-AI through the socioenactive system. The socioenactive scenario involves a socioenactive system based on BCI (Brain Computer Interface) composed of several components: a mind wave device, smartwatch, parrot robot, and Aquarela Virtual system (which involves physical QR toys). These components are connected to share data remotely. The mind wave device and smartwatch collect neurophysiological information, and AI algorithms process this data to recognize emotions evoked by a parrot robot and the Aquarela Virtual. The AI component uses a machine learning technique to recognize emotions in brain waves (EEG) data. Our solution explores tree algorithms to recognize emotions in heart rate (ECG) data. Our evaluation, conducted in a workshop with participants from different nationalities and ages, demonstrates that the socioenactive system with embedded AI is a key driver of socio-emotional interactions. The system's ability to interpret and utilize neurophysiological information to facilitate dynamic coupling between humans and technological processes might significantly advance Human-AI Interaction.

1 INTRODUCTION

Socioenactive systems are an emerging approach characterized by interfaces driven by bodily involvement in scenarios of social-physical-digital coupling (Baranauskas, 2015) (Baranauskas et al., 2024). These systems can consider the human body's unconscious neurophysiological signals (Kaipainen et al., 2011). These signals reflect emotional states transported from the brain to all parts of the human body through the autonomic and cardiac nervous systems (Ivonin et al., 2013) (Smith and Lane, 2015). Although socioenactive systems involve a promising field for investigations considering neurophysiological information, this field has not yet been explored using AI (Rodrigues Filho and Nogueira, 2022).

Moreover, the proliferation of AI has allowed the treatment of these neurophysiological signals. However, questions have arisen about how people interact with systems that contain AI (Jiang et al., 2024). To fill this gap, this research addresses studying human-computer-AI interaction by adopting the socioenactive approach, specifically considering emotional neurophysiological information in human-computer interaction through AI. Therefore, our main objective was to build a socioenactive system that embeds AI, which allows remote socio-emotional interactions among people. To achieve this objective, we review technologies that involve internal aspects of the human body. We found that Brain-Computer Interfaces (BCI) are systems that study human neurolog-

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ical (EEG) information to identify patterns in brain waves. So, once these patterns are identified, the BCI sends commands to a desired action, such as control of a cursor or a prosthetic limb, among others. In this research, we used BCI to recognize emotions in brain waves; besides, we used heart rate information to identify emotions in physiological information. Once the emotion is identified in brain waves and/or heart rate, action commands are sent to the system to evoke socio-emotional interaction between two people who are remotely connected through the internet. The system that includes a parrot robot and the Aquarela Virtual system (Duarte et al., 2022) is intended to promotes emotional interactions between the people who use the socioenactive system. The research questions that we will answer with this study are: (RQ1) Does the socioenactive system embedded with AI, involve an interface driven by neurophysiological and bodily expression? (RQ2) Does the socioenactive system embedded with AI constitute a dynamic coupling between human and technological process? (RQ3) Is it possible to promote remote socio-emotional interactions by unconscious body reactions in socioenactive systems embedded with AI? To evaluate our proposal, we conducted experiments that considered 9 participants (from Brazil, Peru, and Africa). The participants were organized in groups of 2 people to allow remote interactions among them. The system, through a smartwatch (ECG) and mind wave (EEG) devices, collected neurophysiological information, and the AI analyzed the neurophysiological information and sent commands to the parrot robot and Aquarela Virtual system when emotions were identified in brain waves and heart rate. We evaluated the neurophysiological information to identify the number of times that the system recognized emotions and the number of emotional interactions that the system promoted among the participants.

The results showed that the socioenactive system, through the AI, recognized emotions in participants' neurophysiological information and sent commands to the parrot robot and Aquarela Virtual to express voice emotions and animations. These interactions through the system allowed socio-emotional interaction to appear among the participants. In conclusion, the socioenactive system enriched with AI drove socio-emotional interactions, expressed by neurophysiological and bodily involvement. In this process, a dynamic coupling between human and technological processes that involved AI was developed.

This article is organized as follows. Section 2 presents a literature review. Section 3 describes the socioenactive system built to promote remote socio-emotional interactions. Section 4 describes how AI is embedded in the socioenactive system. Section 5 presents a case study, the participants, the methods used, and the evaluation of results. Finally, the discussions 6 and conclusions 7 follow.

2 RELATED WORK

We explored the literature about studies related to AI and enactive/socioenactive systems, and a few works (Rodrigues Filho and Nogueira, 2022) were found regarding these fields. Then, we looked for studies that involved AI, emotions, enactive, socioenactive, and BCI. We found two studies (Kaipainen et al., 2011) and (Gonçalves et al., 2021) that involved the enactive/socioenactive field, AI, and emotions. We found the studies of (Wang et al., 2020) and (Jiang et al., 2019), which are related to BCI and AI. The study of Kaipainen *et al.* (Kaipainen et al., 2011) is an interesting research that shows an enactive system based on human psychophysiological reactions. The system mounts a film based on a person's psychophysiological expressions. The system is built with minimalist aspects and uses facial electromyography (EMG), heart rate (HR), and electrodermal activity (EDA) to measure emotional expressions. The film is mounted by the system based on psychophysiological expressions and a spatial ontology. The ontology contains a repertoire with notations and some automated analysis. This study aimed to show how unconscious interaction can occur in the interaction of human-computer. Despite this work being an excellent reference for our research, it does not tackle the social aspects. The research proposed by Gonçalves *et al.* (Gonçalves et al., 2021) presented an architecture of a socioenactive system with AI. The AI in the system is used to recognize emotional states in participants' faces. Despite this study involving AI and socioenactive systems, it was still exploratory. Wang *et al.* (Wang et al., 2020) involved the human-AI interaction promoted by BCI and a neurohaptic interface. The system was built to connect two remote people through the internet. The two people wear a BCI (based on EEG) device and a haptic armband. When the system recognizes an emotion from one person, "feelings of missing someone," the system transmits commands to the haptic armband of the remote person. The system shows the image of the person who transmitted the "missing you" signals to the remote person on a screen. As we can see, the system allows human-AI emotional interactions; however, this study does not explore the socioenactive aspects of interaction. Jian *et al.* (Jiang et al., 2019) also involves BCI in social interactions (multi-person brain-to-brain). They show the power of brain waves in social interactions. In this study, three people interacted by playing the Tetris game remotely; the participants, through their brain waves, sent commands to the system to turn the block in the Tetris game. Considering a conventional social network, this work shows a social network of brains connected to interact between them through thinking. The results point to future brain-to-brain interfaces that enable cooperative problem-solving by humans using a "social network" of connected brains. Although this study involves BCI and AI, they do not delve deep into the socioenactive field of socio-emotional interactions. Existing studies are focused on the field of socioenactive/enactive or BCI, but there are no studies that combine these two paradigms. On one side, the BCI studies show that neural data are relevant in social interactions. Thus, technological devices could give us brain and body internal neurophysiological information. On the other hand, socioenactive perspectives study and use neurophysiological information in social interactions, but there are not yet profound studies in this field. Therefore, this gap shows an opportunity for this research project.

3 BUILDING A SOCIOENACTIVE SYSTEM BASED ON BCI

We define a scenario by considering socioenactive dimensions (social, physical, and digital) to build a socioenactive system.

3.1 A Scenario for Socio-Emotional Interactions with AI

When we contact an animal, we often become uninhibited in expressing our emotions because they unleash an immediate and natural emotional response in us (Gee et al., 2017)(Fellous, 2004). This is why they are usually used in therapies. Our proposal scenario involves a toy parrot as an object embedded with technology. Figure 1 shows the technological components of our experimentation scenario.

In the scenario, at least two participants are remotely connected via the internet, facilitating communication and interaction. One of them uses a wristband and a headband as wearable devices. Objects with embedded ubiquitous technologies, like parrots, are used for experimentation. A system is set up on the laptop to control the technological components. The technological devices (wristband and headband) and objects embedded with technology are

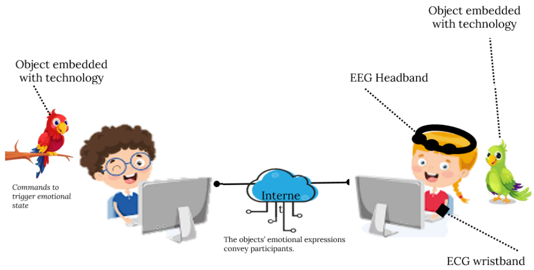

Figure 1: A scenario for socio-emotional interactions with AI.

linked to the computer. This scenario intends to join two remotely connected people and promote socio-emotional interactions through the proposed socioenactive system. Through this scenario, we can study the AI interactions and coupling between humans and the socioenactive system with AI.

3.1.1 Building the Socioenactive System

Considering the previous scenario, the building of the socioenactive system involves focusing on the digital dimension, taking into account the physical and social dimensions. Therefore, the artifacts defined and designed for the socioenactive system involved a mind wave, a smartwatch, a parrot robot, and the Aquarela Virtual system ((Duarte et al., 2022)). These artifacts involve devices and computational systems with different programming languages and operational systems, which adds complexity to the system's development. Therefore, we used an architecture based on components to build the socioenactive system, and it involved the following technological components:

- **Brain Wave Component.** This is the headband (wearable device) that allows catching brain wave data, specifically EEG information. The information collected by this device is stored in a computer.
- **Smartwatch Component.** This is the wristband, which is a wearable device that allows the collection of heart rate data, precisely ECG information. The information gathered by this device is stored in the smartwatch's memory.
- **Controller Component.** This is a component in charge of managing or directing the input and/or output data flow between the components as a function to command the components.
- **EEG Component.** This component is in charge of processing the data collected by the brain wave component, sending this data, and receiving commands from the AI component. This application connects the brain wave component and the AI component.

- **ECG Component.** This component allows the collection of preprocessed heart rate data in real-time from the smartwatch. Besides, it includes an algorithm to identify emotional states in heart rate data. The algorithm result is sent to the *controller component*.
- **AI Component.** This component contains an AI algorithm. It allows for identifying emotional states in brain waves. The result of this component is sent to the *controller component*.
- **Aquarela Component.** Aquarela Virtual is a system created and developed by the (Duarte et al., 2022). It is a web application that allows remote socio-emotional interactions between people. This application was built to allow physical activities among children to be geographically distributed. Besides Aquarela being a web application, it involves body expression and interaction through playful physical objects. This paradigm differs from using mouse, keyboard, and touch screen in conventional web applications. It uses objects with QR codes, which are perceived computationally by the application to evoke socio-emotional interactions among the participants. We adapted and connected the Aquarela system to build the Parrot's scenario to attain our purposes. As a result, we got the Aquarela component, which was connected to the *controller component*. The emotional state identified by the AI component is sent to the *controller component*, and it triggers an emotional state to the *Aquarela component* to initiate a sound and animation of the emotional state.
- **Parrot Robot Component.** This component is an object embedded with ubiquitous technology (Raspberry Pi). The object has the color and shape of a blue parrot, and it emits sounds like a real parrot, so we call it a parrot robot. It has the function of triggering a sound related to an emotional state. When this component receives an emotional state from the *Controller component*, it triggers an emotional state.

The smartwatch and mind wave components are in charge of gathering a person's neurophysiological information. Two robot parrots and the Aquarela Virtual are in charge of promoting emotional interactions between participants. These components are linked to the laptop/computer through the other components in the system. The BCI involved in the system allows the processing of neurophysiological information collected by the Mind Wave device (EEG) and transforms it into commands. Figure 2 shows the relationship and link between the components.

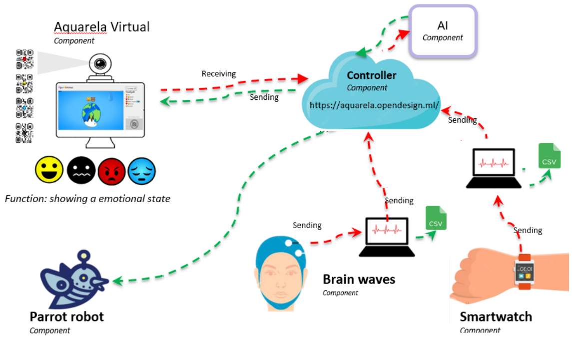

Figure 2: Components built for the socioenactive system in a scenario of socio-emotional interaction with AI.

4 EMBEDDING AI IN THE SOCIENACTIVE SYSTEM

We present how AI was embedded in the previously created socioenactive system scenario. We describe the AI component in the following.

4.1 An AI Model to Recognize Emotions in Brain Signals

We present the steps followed to embed AI in the socioenactive system. The objective was to use AI to recognize emotional states in brain waves in real time in the socioenactive system.

A) Choosing an AI Algorithm

To include AI in our socioenactive system, we have reviewed machine learning and deep learning techniques applied in AI for brain waves. We found more articles using machine learning than deep learning regarding emotion classification/recognition in brain waves (EEG). The literature review results showed that Support Vector Machine (SVM) is a machine learning method largely used as a kernel for classification tools. In the last years, the SVM algorithm has been mainly used in EEG classification to study emotions, as described in articles [(Blanco-Ríos et al., 2024), (Huang et al., 2023), (Jianbiao et al., 2023), (Saccá et al., 2018), (Sai et al., 2017)].

B) Choosing a Dataset

In previous work, we have developed a dataset of emotional brain waves (Espinoza Taype et al., 2023). This EEG brain waves dataset was collected from 21 people and involved basic emotional states: happiness, sadness, fear, and anger, each one with 1201, 1311, 1311, and 1486 records, respectively. The dataset contains frequency bands data: delta','theta','alpha', 'beta', and 'gamma'. These data were analyzed using the Fourier Transform method;

the result showed features in amplitude and frequency to differentiate emotional states in brain waves. Considering this dataset, we continue with the following step.

C) Pre-processing the Dataset

We prepared and cleaned the dataset to make it more suitable for our machine-learning algorithm (which will be shown in the following step). This step aims to reduce the complexity, prevent overfitting, and improve the model's overall performance. The dataset contains data on brain waves of four emotional states: happiness, sadness, fear, and anger. The process used to pre-process the data involved the following steps: removing duplicates, removing irrelevant data, converting data type, clear formatting, fixing errors, and handling missing values.

D) Dataset Organization

In this step, the brain waves data was organized to train and test the machine learning algorithm. We split our dataset into two subsets: training and testing with 70% and 30% of data, respectively (Uçar et al., 2020). The training data was used to train the machine learning algorithm. The testing data was used to evaluate the accuracy of the trained algorithm. Both data groups contain four data classes: happiness, sadness, fear, and anger, each one with 1201, 1311, 1311, and 1486 brain wave records, respectively.

E) Model Development

For the data pre-processing and the development of the machine learning model, we use the following libraries: Phython, Pandas, Numpy, Matplotlib, Sklearn, and Seaborn.

In the beginning, the model was developed to classify two signal classes (happiness and sadness). Afterward, it was adapted to classify four signal classes (happiness, sadness, fear, and anger). The objective in developing these two models was to identify the levels of accuracy that the model could achieve in classifying two and four emotion types. The results are shown in the next step.

F) Model Results

After the Machine Learning model development, we executed it to get classification results. So, we used the confusion matrix, which is a table used to evaluate the performance of a machine-learning algorithm. It allows us to evaluate the accuracy of the signal classification. The confusion matrix in Figure 3 and 4 show how many samples were correctly and incorrectly classified by the algorithm in each class. The SVM model produced can be accessed in the following link "SVM to classify emotions in brain waves".

Classification of Two Emotions

Figure 3 shows the confusion matrix for a binary class dataset consisting 1201 samples in the positive emotional state class (happiness) and 1663 in the negative emotional state class (sadness) of the test set.

In Figure 3, the SVM algorithm accurately predicted 357 brain waves as positive emotion (happiness) and 196 as negative emotion (sadness). However, 146 brain waves were misclassified as negative emotions when they were positive, and 161 were incorrectly classified as positive emotions when they were negative emotions. Therefore, the prediction was 69% of precision for happiness emotion (positive emotion) and 57% for sadness emotion (negative emotion).

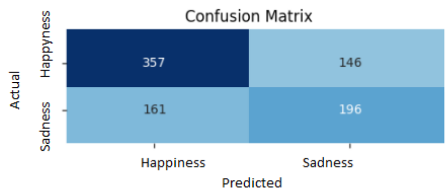

Figure 3: The SVM algorithm prediction accurately predicted 553 (357 happiness, 196 sadness) brain waves and misclassified 307 (161 happiness, 146 sadness).

Classification of Four Emotions

We have carried out the SVM algorithm again for multiclass classification, this time with four emotions: happiness, sadness, fear, and anger. The dataset was composed by 1201, 1663, 1486, and 1311 brain waves for happiness, sadness, fear, and anger emotions. The results show precisions in predictions of 28%, 38%, 27%, and 25% for happiness, sadness, fear, and anger, respectively. Figure 4 shows 38, 237, 206, and 40 brain waves correctly classified, while the remaining brain waves were misclassified.

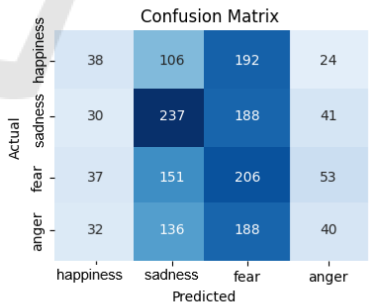

Figure 4: The SVM algorithm prediction of happiness, sadness, fear, and anger emotions.

We observe that the accuracy in classifying two emotional states is better compared to classifying four emotional states. According to (Mathur and Foody, 2008), a multiclass classification may require more major support vectors than a binary class, which means, it requires a series of optimizations and classification parameters for multiclass. In an evaluation of multiclass classification, (Foody and Mathur, 2004) states that SVMs were originally defined as binary classifiers, and their use for multiclass classifications is more problematic. So, it is necessary to use strategies that could reduce the multiclass problem to a set of binary problems. Multiclass problems are commonly encountered. Currently, researchers are addressing to board this problem (for instance, (Ke et al., 2024), (Nie et al., 2024), (Lai et al., 2024), among others).

G) Embedding the AI Model in the Socioenactive System

After developing, training, and getting the model's results, the next step involves embedding the model in the socioenactive system. For this purpose, we followed the next steps:

- **G.1 Zipping the Model**
  To use the model in applications, we compress and serialize it using the joblib and pickle libraries in Python. The zip model is now ready to be used like a box containing inputs and outputs. So, it is possible to send brain wave values to this box, and it will respond and answer (with the emotional state identified).
- **G.2 AI Application**
  After compressing the model, we developed an application that contains the zip model, which is connected to the whole socioenactive system. We used the Flask framework to develop the application. As a result, the AI application is connected to the whole socioenactive system, which allows it to receive brain wave data and respond to an emotional state. The application is available in the following link AI application to classify emotions in brain waves
- **G.3 Model Implementation**
  After creating a ML model to classify emotions in brain wave signals, the next step was to deploy the model on a server.

4.2 Emotion in Heart Rate

After implementing the AI based on brain waves, we added heart rate physiological measurements to improve the AI results. So, we worked with the ECG component (Smartwatch).

We inquired about heart rate peaks to extract knowledge from the heart rate signals collected by the smartwatch application. According to (Pollreisz and TaheriNejad, 2017), the peaks always have similar heights. Hence, the peaks were categorized into two groups with different heights. A peak's height is lower than 100 is classified as a slight peak; if it is higher than 100, it is considered a significant peak. The rationale behind the value 100 involves estimations using the max value in the sequence of heart rate. Thus, we analyzed all signals, and whenever a small or large peak was detected, its respective counter was increased. These statistical analyses were then used to categorize the signals into two groups: (i) Signals with a height over 100 as happiness emotion, and (ii) signals with a height lower than 100 were classified as sadness emotion. 5) Classification: The classification is done via a decision tree based on statistical information. First, it starts by analyzing the peaks. For example, if there are sequences of significant peaks in the measured signal, a counter is increased for the happiness emotion. However, if there are minor peaks in the signal, the counter for the sadness emotion is increased. At the end, the probability of occurrence of each emotion is calculated in percentage based on the value of the counters for each emotion.

This algorithm was joined with the AI developed previously to give autonomy to the socioenactive system regarding the decisions of emotion recognition in neurophysiological information.

5 CASE STUDY: SOCIO-EMOTIONAL INTERACTIONS PROMOTED BY A SOCIOENACTIVE SYSTEM WITH AI

To experiment with the socioenactive system embedded with AI, we carried out a workshop at the University of Campinas (UNICAMP). The workshop lasted one week, with one day as the main one (Saturday). During the workshop week, we invited students/people to volunteer and experience the system. One day, two students from the UNICAMP (age 20-23) participated, and on the main day, seven children between 5 and 10 years old participated, accompanied by their parents/relatives.

5.1 Methods

In the experiment, two participants were remotely connected via the internet through the socioenactive system, each one of them in a different ambient. One participant wears the smartwatch and mind wave devices on his wrist and head, respectively. In each ambient, a parrot robot, physical toys with QR codes, and a screen to display the Aquarela Virtual were placed around each participant. To capture facial, vocal, and postural expressions, cameras were positioned in front of the participants to record their movements and body language. Additionally, Google Meet was utilized to record the participants during the interaction.

A participant began interacting with the physical QR toys and the parrot robot, holding the QR toys up to the laptop's camera. Through this action, the participant shares their emotions and engages with the other participant on the opposite side and also with the parrot robot and Aquarela Virtual. Considering the emotion shared by the participant, the parrot robot triggers voice emotional expressions, and the Aquarela Virtual playes sounds showing animations with digital emotional emoticons and toys. Intrinsically, the physical toys with QR codes inspired emotional features through their designs and colors.

The socioenactive system, through the smartwatch and mind wave devices collected the participants' brain wave and heart rate data (when they were interacting). In real-time, the system (with the AI) processes the collected data to recognize an emotional state; thus, when an emotion is identified, the system triggers socio-emotional interactions to the parrot robot and Aquarela Virtual. It means, the AI worked during the experimentation, identifying participants' emotional states from the neurophysiological information and transforming these signals in the parrot robot actions and reactions in Aquarela Virtual.

5.2 Evaluation Results

The analysis of neurophysiological information collected by the Mind Wave (EEG) and Smartwatch (ECG) shows the results in Figures 5 and 6 respectively. For instance, considering the EEG analysis, from 2671 brain waves, the happiness emotion was identified 14 times in child one. From 782 brain signals in student number one, 12 times the AI identified happiness emotion. In child number two, from 2316 brain waves, 21 times were identified as happiness emotions. Child number three had 14 brain waves collected, but unfortunately, she had several buns in her head, and she did not want to use the mind wave device, so it was impossible for the AI to identify emotions in brain waves. Regarding heart rate (ECG) analysis (Figure 6), child number one recorded 1460 heart rates and 5 times was identified happiness emotion. For child number five, 100 heart rates were collected, and 5 times were identified the happiness emotion. In child number three, 14 heart rate signals were collected; unfortunately, the child pushed some buttons in the smartwatch and stopped the data collection.

As we can see, emotional expression of happiness was identified in brain waves and heart rate signals, while other emotions (sadness) were not identified. We could corroborate these results through the analysis of the self-report questionnaires filled out by the children (with the help of a relative/monitor) before and after the experimentation in the workshop (Figure 7). The self-report questionnaire shows an increase in happiness emotion after the socioenactive experience from 5 to 11, while the other emotions (sadness, fear, and anger) remain in the same value in child number (1) (Figure 7 shows these results). In child number three, happiness went from 5 to 10, while negative emotions disappeared. For child number five, happiness increased in 6, and negative emotions reduced in 4. Student number one (1) 's happiness increased from 4 to 10, and negative emotions remained at the same value (3).

The analysis of facial, voice, and postural expressions also showed an increase in emotional expressions in participants (Figure 8). For instance, child number one showed 63 times facial/voice/postural expressions of happiness while others emotional expressions were 12 times. Child number three and five showed 45 and 11 times facial, voice, and postural expressions of happiness respectively. Student one showed 9 times happiness expressions. Figure 8 shows these results.

These results show that the happiness emotion (positive) was expressed by neurophysiological and body (facial, voice, and postural) expressions. When we analyzed the socio-emotional interactions with the system, we could identify that the participants used the physical objects (toys with QR codes) to share emotions between them through the system. Figure 9 shows the times when the participants interacted intentionally (consciously), sharing emotions using the QR toys through the system. For instance, child 3 interacted 22 times emotionally through the toys; from them, 7 were happy, and 15 were in negative emotions (sadness, fear, or anger). Child number one shared happiness emotions 6 times and other emotions 2 times. Child number five interacted happily 7 times, while 5 times were other negative emotions. Student one was 3 times happy, and 1 time felt another emotion.

5.2.1 Regarding the Socioenactive Coupling

In spite of our brain and body's emotional expressions being a complex phenomenon, we could synthesize the following: the brain expresses emotions through neuron excitation, neurotransmitters in charge of transmitting the signals excitation from neuron to neuron generating electrical impulses in the

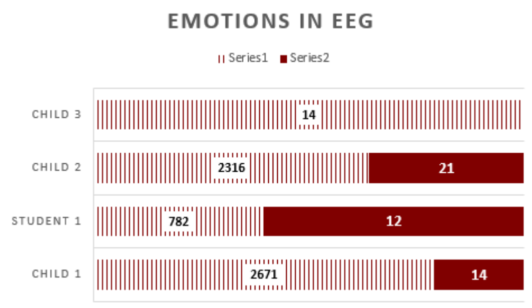

Figure 5: Emotional expressions identified by the AI in brain wave.

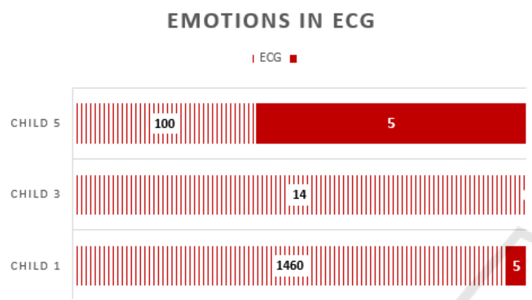

Figure 6: Emotional expressions identified by the AI in heart rate.

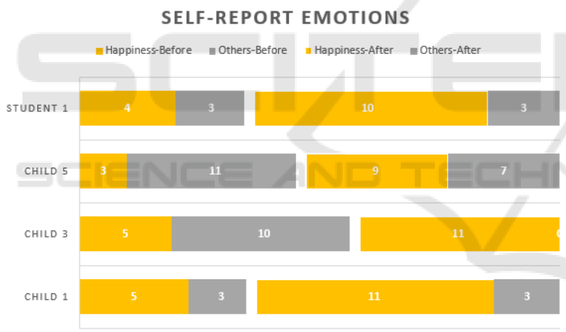

Figure 7: Self-report questionnaire filled by the participants stating their emotional states before and after the socio-emotional experience in the workshop.

brain which we collect through the Mind Wave (EEG device component). Our body expresses emotions through heart rate intensities, whereas blood is lob with intensities to the body and brain. The Smartwatch (ECG device component) collected this heart rate data. Thus, these brain and body signals become emotional neurophysiological information that is transmitted through the socioenactive system and internet from person to person. The emotional neurophysiological expressions from one person become emotional expressions in the other person (voice, face, body emotional expressions). As a consequence, the neurophysiological emotional contagion was promoted by AI.

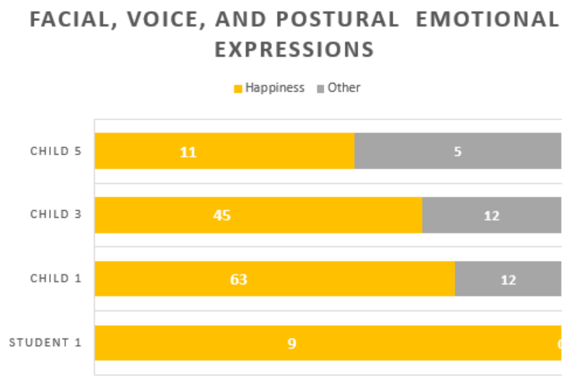

Figure 8: Body (facial, voice, and postural) emotional expressions identified in the participants during the experience with the socioenactive system in the workshop. A camera recorded the participant's facial, voice, and postural expressions.

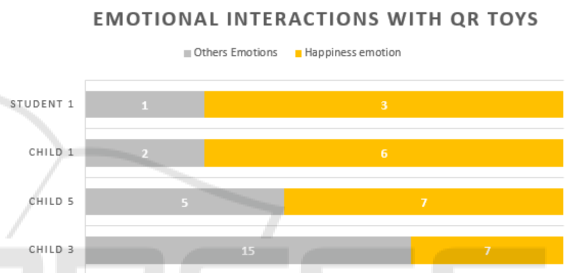

Figure 9: Emotional interactions identified by the system when the participant interacted with the QR toys (through the lecture on QR codes stuck in the toys).

The experimentation in the case study showed us that socioenactive participation involves the continuous coupling of different points of interconnections between humans and computers in socioenactive environments. Externally and internally, our body interacts with other humans and physical objects on a conscious and unconscious level. Externally, our body expresses emotions through our facial, postural, and voice expressions. Besides, internally, our body and brain, through the cardiac system, neural system, other systems, and organs, are involved in a dynamic process in which we express emotions through neurophysiological reactions. It means our body and brain involve internal and external dimensions, that are conscious and unconscious of interactions with humans and physical things. The socioenactive coupling allows us to surpass these dimensions from internal to external and from external to internal orbits in dynamic, continuous, complex, and infinitive feedback loops through perception, cognition, sensorimotor, and emotions. This means that dynamic loops between the human brain, body, hands, eyes, and so on, and the space surrounding him/her shape an interwoven and fluid dynamic process that is constantly forming and re-forming over short periods of time. This complex dynamic system reshapes, re-wires, and re-models the human brain and body, which is called embodiment.

The socioenactive system allows explicit, intentional, conscious, and implicit unconscious control of the system, which allows participants to interact by embodied action. The interaction involved is conscious and intentional, controlled by embodied action, and unconsciously controlled by the body's neurophysiological reactions. The conscious side was managed by body action when the participant interacted with physical objects (showing the QR toys to the camera) to share emotions through the system. The unconscious side was managed by the system through the smartwatch, mind wave device, and the AI algorithm. The challenge was on the unconscious side to recognize emotions in brain waves and heart rate in real-time. The AI embedded in the socioenactive system allows the interpretation of emotions from neurophysiological reactions, which allows the system to adopt a dynamic and autonomous behavior. The socioenactive system acted as a mediator of the emotional dynamic coupling between the participants connected remotely. The AI in charge of interpreting emotions in the brain and heart rate gives to the system emotional behaviors. It means the system acted and reacted based on the conscious and unconscious emotions of the participants in a coordinated way with its components (smartwatch, mind wave, parrot robot, Aquarela Virtual, and whole socioenactive system).

For example (Figure 10), when the AI recognizes emotion in a participant's brain waves or heart rate, the system coordinates with the parrot robot and Aquarela Virtual to play emotional sounds and displays emotional animations with digital emoticons. Thus, the participants may express in the system unconscious personal emotions from neurophysiological actions, transmitting them to other participants who are connected remotely. The other participants expressed conscious emotions using the QR toy. Then, the system allows a recursive interaction between the participants at conscious and unconscious levels.

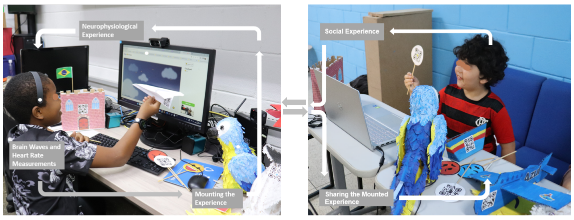

Figure 10: Emotional interactions between participants at conscious and unconscious levels.

The dynamic montage (Figure 10) of the system is mapped considering the neurophysiological emotional expressions and body action expressions (when the participants interact through toys with QR codes). The system includes sequential instructions and decision algorithms, in charge of the dynamic montage. Figure 11 shows when two participants interacted emotionally through the system remotely; on the left side, a participant using the smartwatch, mind wave, and the toys with QR is transmitting emotions to the participants on the right side. The participants on the right side answered by sending emotions through the interaction with the emotional toys. For instance, child one's EEG reflected 14 times emotions, his ECG 5 times, and his emotional interaction with the toys showed 8 times; these emotions were transmitted through the system to child number two. This child (2) answered child number one with emotional interactions through the QR toys 13 times. The same occurred with the other participants; child number three sent 21 (EEG), 5 (ECG), and 22 (toys) emotional expressions to child number four, who answered with 11 emotional expressions through the toys. Child number five expresses her emotions through the toys 12 times, and she receives 10 times emotional reactions (through the toys) by child number six. Student number one transmitted emotional expressions, sending 12 (EEG) and 4 (QR), having a response of 4 times (QR) from student number two. Therefore, answering the (RQ2) " Does the socioenactive system embedded with AI constitute a dynamic coupling between human and technological process?", the answer is yes because the system allowed dynamic coupling of coordinated actions between two participants. The emotional expressions (neurophysiological and bodily involvement) from one participant become impressions (that at the same time become emotional expressions) for the other participant.

In order to answer the research question (RQ1), " Does the socioenactive system embedded with AI involve an interface driven by neurophysiological and bodily expression?", the answer is yes because the socioenactive system through the AI (EEG and ECG measures) and QR toys recognized emotions in participant' neurophysiological signals and bodily involvement, driving socio-emotional interactions to another participant who was in another remote ambiance. The interface driven by neurophysiological and bodily involvement occurred 19 (EEG and ECG) and 8 (QR toys) times in child number one. Child number three had 26 (EEG and ECG) and 22 (QR toys) interactions driven by neurophysiological and bodily involvement respectively. Child number five had 12 interactions by bodily involvement (with QR toys). Student number one had 12 interactions by EEG and 4 interactions by QR toys (Figure 11).

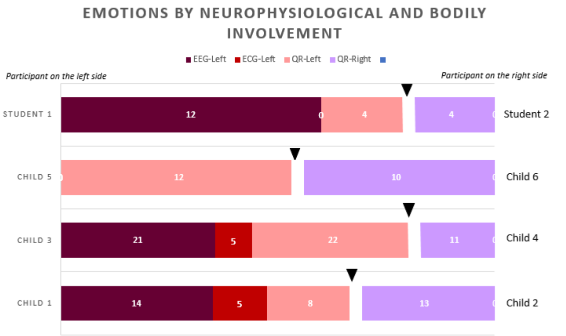

Figure 11: Emotional expressions of happiness in brain waves, heart rate, body (facial, voice, postural) expressions, and self-report questionnaire.

As a final result, and answering the (RQ3) "Is it possible to promote remote socio-emotional interactions by unconscious body reactions in socioenactive systems embedded with AI?" The answer is yes; the socioenactive system, through a person's neurophysiological body responses, facilitates emotional interaction with another individual and physical objects (such as the robot parrot) located in a remote environment.

6 DISCUSSION

The EEG and ECG (neurophysiological) emotional measures showed different variations by each participant. In some participants, the EEG and/or ECG measures were more intense compared to other participants. According to Stenberg (Stenberg, 1992), these variations are affected by the personality and can vary in each participant, affecting the EEG and ECG measurements made by the AI.

The analysis of self-report questionnaires, neurophysiological information, bodily actions, and facial, voice, and postural expressions showed relationships in emotional expressions.

The socioenactive system allowed remote communication by conscious and unconscious body reactions to participants in remote environments through neurophysiological signals.

The data analysis and results showed that the socioenactive system achieved coupling regarding human-computer-AI in unconscious (neurophysiological) and conscious (bodily involvement) levels. The coupling originated from the brain and body of one participant to reach the brain and body of the other remote participant through various dynamic processes and components of the socioenactive system (described in Section 5.2.1).

7 CONCLUSION

This research demonstrated how to embed a socioenactive system with AI and the steps that involve this challenge. Our solution used the SVM algorithm to recognize emotional states in neural information collected by a Mind Wave headset. Our study added a decision tree algorithm to the AI to identify emotions in heart rate (ECG) data collected by a smartwatch. Emotion recognition involves neural information and other physiological information. The experiment results showed that the socioenactive system embedded with AI allowed socio-emotional interactions driven by participants' neurophysiological information and bodily involvement.

Future work involves exploring different feature extraction and learning methods for AI to improve the accuracy of the induced classifiers. Furthermore, the dataset could be improved by applying data augmentation techniques and adding data.

We are now working on an ongoing project to propose a framework that guides the building of such socioenactive systems. The information (dataset and code) produced in this study can be accessed at the following link: https://evelynespinozataype.github.io/romotica/.

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