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Design of Socioenactive Systems Based on Physiological Sensors and Robot Behavior in Educational Environments

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Abstract

Computational systems based on ubiquitous and pervasive technology present several challenges related to the interaction of people with scenarios constituted by sensors and actuators, changing the mindset of what we used to understand as interaction with a computer. This also has influence in the ways of considering the design of systems based on contemporary technology for the educational context. To cope with the challenges of ubiquitous computing, the concept of socioenactive system is being constructed as a system in which human and technological aspects are coupled together in a cycle of perceptually guided actions of people interacting with elements of the physical environment and with other people in the same scenario. In this work we address the design of a socioenactive system as an evolution of two previous systems designed and experimented with 5-year-old children in an educational context. The contribution of this paper is twofold: 1. We present an analysis of two different systems tested in educational scenarios, pointing out the lack of elements that should be present in a complete cycle of socioenactive systems, suggesting requirements for a third system; 2. We present an architecture for the third system and a simulation of its usage. Results of the third system and its simulation inform the next activities of bringing it to real life in a practice proposed for the same audience and context as the previous systems.

Keywords: *Pervasive systems; Educational Technology; Enactivism; Children Interaction; Socioenactive;*

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1. Introduction

Ubiquitous computing involves the design of systems with sets of sensors and pervasive devices that consider adaptability in everyday tasks and invisibility, such as wearables with informational devices or sensors that help to inform something about the environment or the user (Weiser, 1999). This type of technology is also used in the construction of an enactive system, recursive by nature, that involves the feedback loop in which technology has impact on the human agent as well as receives the effect of the human experience on the system, as the system adaptability and behavior changes (Kaipainen et al., 2011). This relationship that transforms the system through people's actions coupled to the system usually should consider not only the individual aspects of this coupling, but the social aspects as well.

From this requirement, the concept of socioenactive systems (Baranauskas, 2015) emerges drawing on the ubiquitous computing paradigms added to the enactivism approach to cognition (Rodriguéz et al., 2014; Varela et al., 1992; Maturana & Varela, 1992; Kaipainen et al., 2011), considering the aspects of actions and social behavior altogether (Baranauskas, 2015; Caceffo et al., 2019; Valente et al., 2020; Valente et al., 2021; Baranauskas et al., 2021). In the socioenactive view, more than one system is affected by a social group who in turn have their behavior affected by the systems.

Some challenges present in socioenactive systems are in the construction of an open system, which can be changed dynamically based on the user's behavior and the construction of a database. Brochado and Carvalho (2021) argue that active methodologies combine the concepts of educational theories with the need to renew the subject, objects and teaching environments (Brochado & Carvalho, 2021), highlighting learning through problems and learning through teams. These concepts are present in socioenactive systems and can serve as educational tools that work through human actions and social experiences (Valente et al., 2021).

The socioenactive systems presented in the literature still lack some features of enactive design such as the dynamic evolution of the system at runtime and the influence of users directly through data such as physiological readings or tracking and identification of behavior, emotions, among other features tracked from users. These features are important to ensure an experience based on the human dimension that considers social behavior promoting learning through actions in a dynamic way through pattern recognition and computational intelligence. According to Gimenez and Merino the knowledge acquired "doing" in enactive systems is more motivating and fun than traditional learning methods and is retained during more time (Jiménez & Merino, 2017).

This research is part of a larger project that aims at designing socioenactive systems (Baranauskas, 2015). In this work, two workshops within an educational scenario are analyzed, as instances of socioenactive systems, according to the concept proposition. From the design of these two workshops, this work presents a proposal to build a next scenario that evolves the results obtained so far and meets the characteristics of a complete cycle of a socioenactive system. This cycle considers that people's interactions change the system that integrates the effects of their actions into its processing. Likewise, the behavior of the system enables changes in people's actions, creating an organic environment and fostering social interactions.

The socioenactive system S1 (Valente et al., 2020) is part of a robot-based workshop that instantiates a proposal for a socioenactive system; in the scenario of S1children, based on the "Little Red Riding Hood" adapted narrative, had to interact among themselves and coordinate their actions to help a robot to find a goal spot in the environment. They wore boots that were used to interact with the robot, a customized mBot[1], developed based on the co-design methodology (Baranauskas et al., 2013). The study with the children was conducted using the action-research method, implemented in a school setting with kindergarten students. The workshop results show that this activity was able to engage children and demonstrate how they behaved as a group to solve a particular task in a socioenative environment.

A second socioenactive system, S2, designed to identify factors and system elements that lead to a socioenactive environment, was instantiated through a practical workshop (Caceffo et al., 2019). This system was based on the definition of a behavior ontology matrix that supports the generation of real-time feedback. This workshop also uses the mBot and a wide range of sensors in order to detect and track participants' behavior.

The previously developed systems (S1 and S2), focused on specific aspects of the socioenactive model, such as those that enable interactions between participants and the use of pervasive technology. Nevertheless, they do not meet completely the requirements of a socioenactive system, mainly in relation to its system adaptability and the technologies involving biological inputs and the feedback based on user data, as responses based on user behaviors and actions at runtime. The expected contribution of this work is to fill this gap with the proposal of a Socioenative system that contemplates both sides of the enactive cycle, followed by simulations of the proposed architecture.

The text is organized as follows: Section 2 presents the background and main concepts underlying this study; Section 3 presents the analysis of S1 and S2 to evolve into S3; Section 4 presents the S3 and its simulations in order to validate the proposed architecture and discusses the preliminary results. The work ends with a conclusion and directions for future works in Section 5.

2. Background and Method

The methodology used to build socioenative systems in educational environments is based on the Socioenactive Educational System (SEES) Framework, that draws on the socioenactive theory, learning theories, and experimentation to enable the design and development of socioenactive educational systems (Imamura et al., 2019). The framework representation is based on Peirce's sign representation (the concepts of object, *representamen* and interpretant) and the three levels of systems (informal, formal and technical) (Stamper et al., 2000). To build systems based on the SEES framework, nine steps are suggested, as shown in Figure 1: 1-learning objective; 2-pedagogical methodology/practice in a culture; 3-activity for target audience; 4-collective behavior; 5-enactive environment; 6-physical-virtual setting; 7-interactions; 8-multimedia content; 9-physical-virtual environment. The first three steps, learning objective, pedagogical methodology and activity, represent the informal system of the SEES. Most of the concerns are related to the general context of the educational system in its culture, beliefs and commitments. The solution should start at this level.

Steps 4 to 6 represent the formal system of the SEES. They encompass the bureaucracy and norms of the infrastructure that will be provided to SEES. The questions related to those steps will address the process of knowledge construction among people and the theoretical aspects of socio-enactivism in the system. The last steps, from 7 to 9, represent the technical system of the envisaged solution. They are concrete and tackle the prototyping design process and how it will

[1] mBot is a STEAM education robot for beginners, that helps in teaching and learning robot programming. Retrieved from https://www.makeblock.com/mbot in 03/05/2021

materialize the solution. In this paper, as we deal with the evolution of previously experimented systems, we inherit some of these steps from the two previous workshops and systems S1 and S2, to focus on the S3 system.

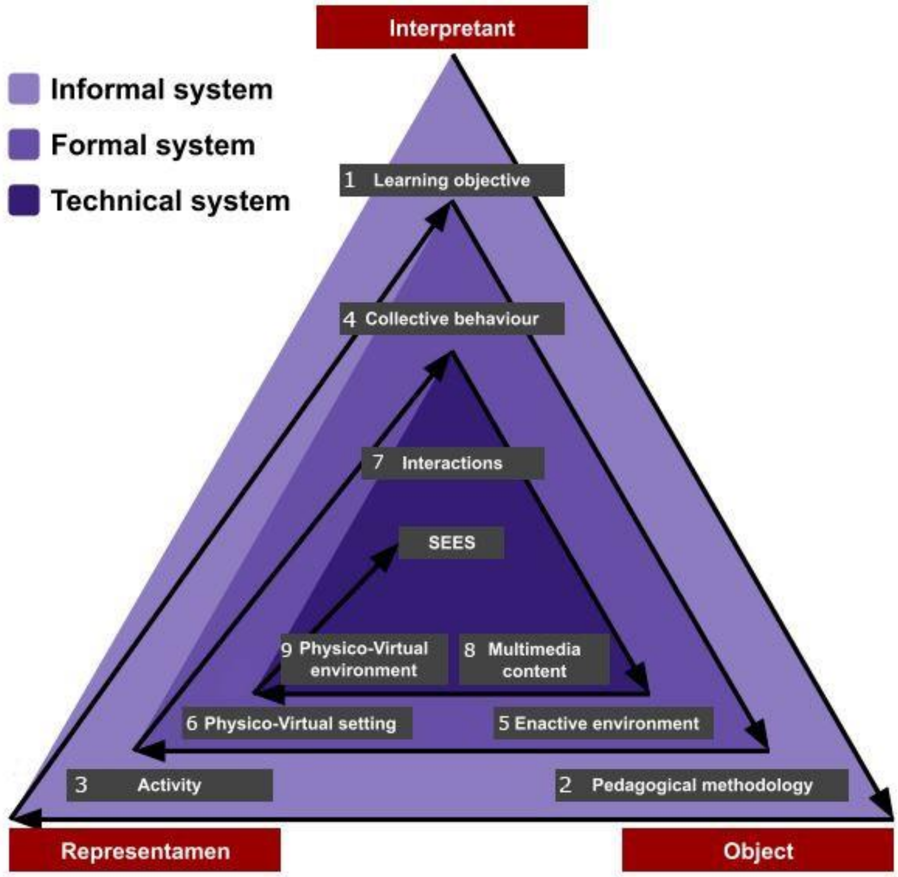

Figure 1. SEES Framework (Imamura et al., 2019). At the three edges of the diagram, the object, the representamen and the interpretant of the semiotic triangle. Among them, the nine steps of the model.

We can also look at the steps from the Peirce's sign perspective. The steps that are related to the interpretant, object, and *representamen* can be grouped, as they have similarities. For example, Steps 1, 4, and 7 (interpretant edge) start a new system layer of each cycle, while Steps 2, 5, and 8 (object edge) are the steps to consider information structure and how it can be turned into action; and, Steps 3, 6, and 9 (representamen edge) can use HCI evaluation and designing tools to raise more information about the materialized system in different levels (informal, formal and technical).

Taking specifically the work related to the *representamen* (steps 3, 6 and 9), the categories that consider physical aspects can be added to an environment based on ubiquitous computing systems through physiological reading sensors that allow to consider human aspects in an involuntary way, guiding changes in the systems of the environment. Social systems usually use physiological reading sensors to indicate to the technological environment information such as people's affective state or behavioral variations due to interaction with the technological environment (Fortenbacher et al., 2017; Lugmayr & Bender, 2016).

Regarding the enactive environment (step 5), Kaipainen et al. (2011) organized objectives that could be used to lead the development of enactive systems into guidelines, based on the definition of enactive systems, as follows:

G1: Definition of a database or rule set to support the generation of behavior in real time;

G2: Definition of technologies supported by sensors to detect and track participants behavior;

G3: Mapping between psycho-physiological dimensions of content;

G4: An algorithm to manage the narrative montage in real time.

The next section will present two scenarios based on socioenative design applied to the educational environment, from which we are evolving a new system.

3. The Systems Developed for the Workshops Scenarios

Based on enactivist concepts (Varela et al., 1992; Maturana & Varela, 1992) and enactive systems presented (Kaipainen et al., 2011), two socioenative systems were developed in the educational context (Caceffo et al., 2019; Valente et al., 2020), named here S1 and S2, respectively.

3.1 Brief description of S1

Figure 2 presents the relations among the elements of the S1 system. Wearing the boots (a), the children (b) managed to change the direction of the robot (c), based on the narrative of guiding the Wolf (robot customization) in grandma's laboratory (a target within the environment floor) (d). An algorithm and a laptop (hidden from the scenario) (e) control the robot's behavior and the sound effects of the narrative. The researchers (f) had different roles: as facilitators in the relation of children with the scenario, as observers taking notes of the whole experience, and as managers of technological settings. The children's teacher (g) provided support for their organization during the workshop (Valente et al., 2020).

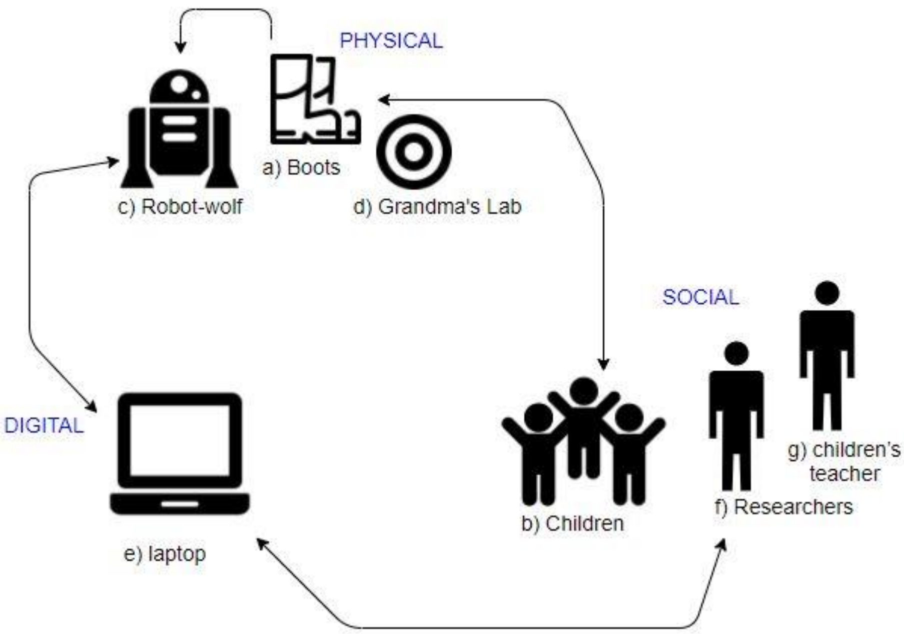

Figure 2. Elements and dynamics of system S1 used in the first workshop.

The system S1 was used in the workshop, which was attended by 26 children between 4 and 5 years old, besides their teachers, and the researchers. The activities were video-recorded and analyzed using the Grounded Theory methodology. The children's behavior was categorized in terms of 4 categories: Awareness, Predictability, Collaboration, and Type of Interaction. This workshop had important results reinforcing how systems with these characteristics promote group work and learning (Valente et al., 2020).

3.2 Brief description of S2

The S2 system was built aiming to evolve S1 to include an ontology matrix capable of feedbacking the computational system, based on the socioenactive concepts. Figure 3 presents the socioenactive elements of S2 that composed the scenario: a robot (a); a "telepathic" box (b) for entering a facial expression of a child (c) which would be communicated to the robot; cards embedded with RFID tags, for children to choose what they guess about the emotion the child expressed in the telepathic box (d). Additionally, the computational system (e) based on an ontology matrix (f), was responsible for feedbacking the system. The researcher (g) in a Wizard of Oz style, decided which action the robot would make based on the child's expression and in the ontology matrix.

A group of 25 children, aged 4 to 5 years old participated in the workshop (Caceffo et al., 2019). The ontology matrix informs the probability of the expressed action to be interpreted by the children, as an ontological solution to represent knowledge about the emotional expressions and a set of behaviors that can be performed by the robot. The system was designed to shape the robots' behavior according to feedback from children's responses in iterative sessions. This entails a complete cycle, where the robot impacts the children and is affected by their experiences.

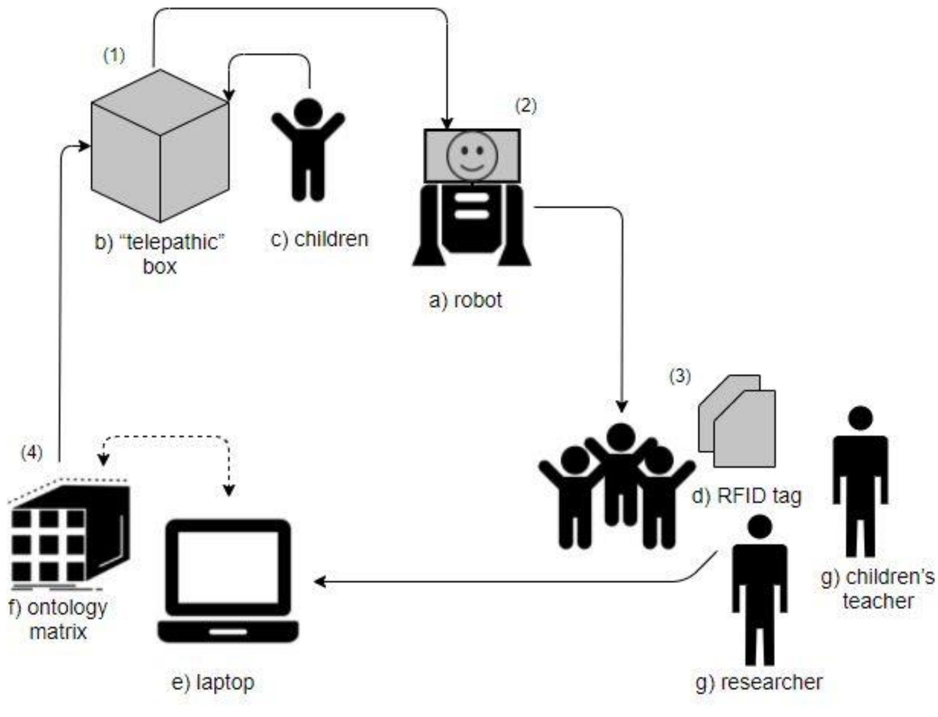

Figure 3. Elements and dynamic of system S2 used in the second workshop.

From a given input, the system analyzes the behavior matrix, processes the data, and provides the appropriate output. Although it presents important results in terms of answering how to integrate ontologies in socioenactive scenarios and the integration of dynamics with real time feedback, S1 and S2 still fail to represent some features of enativism, which led to the proposal of S3.

3.3 Analyzing S1 and S2 under the Socioenactive Dimensions

As explained in section 1, the socioenactive systems S1 and S2 focus on specific aspects of the socioenactive model, whose dimensions are indicated below. Each dimension is composed of a set of requirements, marked in *italic* in the text.

- **Autonomy:** a socioentactive system must be able to be *redefinable by the stakeholders*; *i.e.*, each part involved (users and system designers) can set up and adjust parameters and other variables that change how the system works. Another requirement is that the socioenactive system must be able to *evolve by itself*; *i.e.*, somehow its behavior/internal programming can be affected by the environment, which in response would also affect the environment, leading to a process called the socioenative feedback cycle.
- **Coupling:** the coupling concept in a socioenative system relates to how the input sensors and data are organized and how it affects the system. A requirement is that the system must have *multiple input* ways, *i.e.*, in order to correctly understand the environment that surrounds the system, it needs a set of sensors to retrieve the appropriate data. Additionally, the system must support *physiological human input, i.e.*, be able to automatically read data from the system's users (*e.g.,* through EMG, ECG or EEG sensors, etc.). In a similar way, the system must support *environmental data input*, *i.e.*, be able to retrieve data from the surroundings (*e.g.,* sounds, luminosity, proximity of objects, etc.). In either case, a requirement is that the system's *inputs and outputs are coupled*; i.e., that the input data affects what and how the output data will be perceived.
- **Embodiment:** this dimension relates to the *embodied interaction; i.e.,* the approach in which the users rely on gestures, motion or other ways of embodiment expression to support their communication with the system.
- **Social:** the social element is a key concept in a socioenactive system. A requirement within this dimension relates to the *social interaction* among participants, in which they talk, discuss, collaborate and cooperate when using the socioenactive system. In an educational context, this interaction can support a *collaborative knowledge construction*, in which the group of users realizes some information, strategy or approach that supports a better and more efficient interaction with the system.

Table 1 shows, for each dimension and respective requirements, whether they are covered by S1 and S2 and its justification The requirements analysis comes from discussions about the systems (Valente et al., 2021). In order to measure whether a requirement is covered or not (and to what degree this occurs), the authors discussed the systems based on their own experience using the systems and also considering the related publications. As adherence to a certain requirement is not dichotomic (i.e., the requirement can be partially covered), a scale ranging from 0 (requirement not covered at all) to 1 (requirement totally covered) was adopted. Table 1 illustrates the results of this analysis.

Table 1. Requirements related to each socioenactive dimension. The Table Indicates, for each dimension, whether S1 and S2 cover that requirement and to what extent.

Dimension	Requirement	Is it covered in S1?	Is it covered in S2?	Justification
Autonomy	Redefinable by stakeholder	0.5	0.5	In both S1 and S2, the system designers were able to, if necessary, modify in real time system variables (e.g., in S1, the scratch program could be adjusted, and in S2 the initialization of the ontology matrix could be updated). However, the users (children) were not able to customize the system (e.g., in S1 they were not able to change the mBot speed, and in S2, the mBot sequence of actions related to each expression).
	system Evolves	0	0.75	In S1, the system does not evolve, *i.e.*, every time a group of children start a round (children guiding the mBot to its goal) the system behavior is the same, being only dependent on the children's actions. In S2, after each iteration the system updates an internal ontology matrix considering the children's choices about which expression, they believed the child in the telepathic box had performed. Therefore, each iteration is affected by the previous ones, also affecting the next. An issue of this approach is that it lacks automatism, *i.e.*, the input that updates the ontology matrix comes from each child individual voting, which takes time.
Coupling	Multiple inputs	0	1	In S1 the only input is the mBot's proximity sensor. In S2 there are two inputs: the facial expression performed by the child in the telepathic box and the voting carried out by the children through RFID sensors.
	Physiological human input	0	0	There are no physiological sensors in either S1 or S2.
	Environmental data input	0	0	There is no environmental data input in S1 and S2.
	Inputs and outputs are coupled	1	1	In both S1 and S2, the inputs and outputs are coupled, so the input data affects what and how the output would be. For example, in the S1 when a child puts their boot in front of the mBot, the mBot stops and the system executes a specific algorithm. On its turn, in S2, the expression performed by the child in the telepathic box is the input used to determine (through the ontology matrix) which action would be performed by the mBot.
Embodiment	Embodied interaction	1	0.25	In the S1, in the whole iteration, children wore boots to interact with the mBot. The interaction was spontaneous, guided by the children's perception and the immediate feedback observed in the mBot's actions. In S2, the children's facial expressions were stimulated (not spontaneous), and also the mBot's

				reactions took time to happen, not being immediately noticed by the children.
Social	Collaborative knowledge construction	1	0.25	In S1 it was identified in some iterations that the children were able to organize themselves, defining a strategy to guide the mBot to its goal, which suggests collaborative knowledge construction. In S2 children's actions were individual, either reacting to the mBot's actions as well as voting. There was a natural social interaction between the children after the robot performed its action, and when voting.
	Social Interaction	1	0.25	In S1 children cooperated with each other to reach the goal, also fraternizing when it was achieved and also sharing the emotions of the other moments, even if negative (e.g. the mBot left the forest and hit the trees that surrounded it). On its turn, in S2, although the children had a moment to share their opinions with each other, by the end of each iteration each child individually voted which facial expression he/she believed the child in the telepathic box had performed.

Figure 4 shows how each socioenactive system (S1 and S2) is positioned in relation to each one of the socioenactive dimensions. The data in Figure 4 was calculated considering, for each dimension, the average score of its requirements. For example, in the coupling dimension the S1 average is `(0+0+0+1)/ 4 = 0.25`, and the S2 average is `(1+0+0+1)/4 = 0.50.`

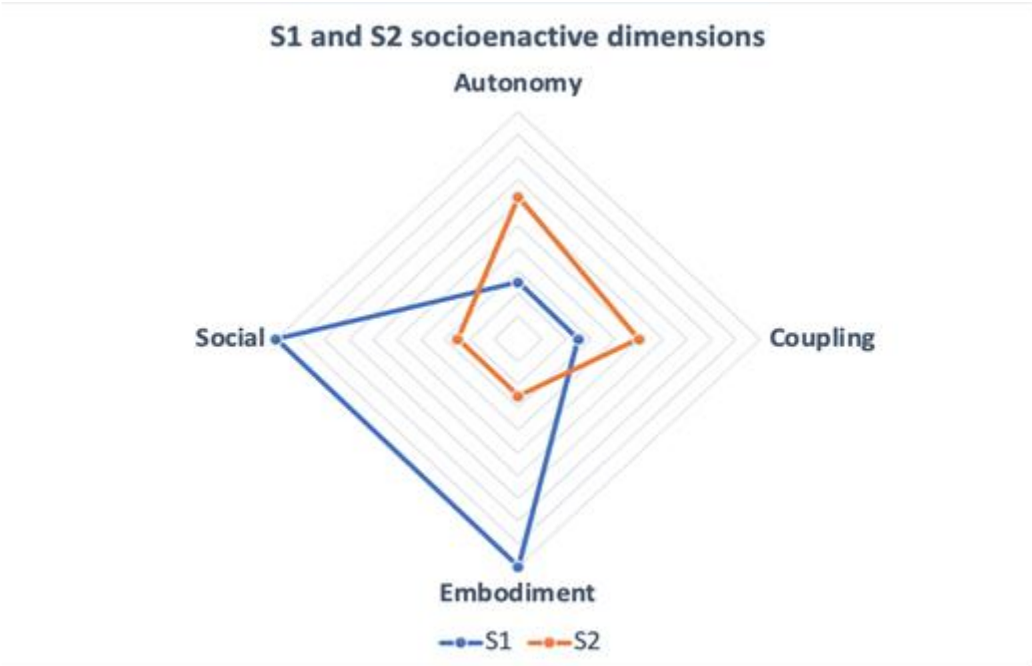

Figure 4. How each socioenactive system (S1 and S2) is positioned in relation to each one of the socioenactive dimensions.

As shown in Figure 4, the system S1 has higher social and embodiment scores, and S2 a higher autonomy. Both systems have a low coupling score, indicating that future socioenactive systems should have more sensors, including *physiological human input sensors* and also *environmental sensors.*

4. Design proposal for a socioenactive system (S3)

This section presents the design proposal for a socioenactive system that contemplates the entire feedback cycle with users and the technological architecture necessary to initiate a workshop with the expected elements of embodiment, ubiquitous computing, enation, and that considers interactions and social activities, shown in section 4.1. Section 4.2 presents a simulation and initial results of the construction of S3 following the proposed model, while Section 4.3 proposes a narrative for experiencing S3 system in a workshop with children.

4.1 S3 System Proposal

In systems based on social environments, we can consider human interaction through physiological readings (Thomas et al., 2017) that provide unconscious data entry, a type of input needed in the socioenative systems cycle. These data can indicate behavior changes concerning emotional states, such as excitement, or physical interactions, through involuntary time series. They are a relevant attribute used as input data for dynamic changes in the behavior of the technological system conducting the experience.

Physiological sensors are commonly present in wearables with embedded technologies, the most common being heart rate-based readers such as: Electrocardiogram (ECG), Heart-rate and Heart-rate-variability (HR, HRV), or Electrodermal activity (EDA), Skin conductance level (SCR), and Skin conductance resistance (SCL) (Brady et al., 2016) (Rahim et al., 2019) (Lazar, 2017). This type of data capture sends signals as numerical list data indicating timestamps and untreated values of the biological reading itself. The treatment of these readings depends on the type of dataset or storage that is sought to be structured, following conventions in a notation language with labels for each different reading and their respective values. These data might include in the system the Physiological human input requirements of the Coupling dimension (cf. Table 1).

Machine learning techniques such as Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) are often used to analyze physiological data. Brady et al. (Brady et al., 2016) use an adapted CNN for Emotion Prediction based on physiological data (Wang et al., 2015). Rahim et al. (Rahim et al., 2019) present a method for emotion recognition with CNN using HR and GSR sensor signals through a scalogram of images generated by physiological inputs, resulting in a good classification rate. In general, these algorithms work by identifying similar sequences and labeling them, updating the hypothesis of Euclidean variation (timestamp and biological reading), classifying the numerical sequence pattern until defining a set of examples.

A simplified model can associate these two types of data (timestamp and variation), classifying patterns in the signals and comparing them with the emotion most present in an action. This type of technique can be used by an algorithm as part of the socioenactive system, generating responses based on the participants' dynamic reactions, respecting the guidelines proposed for enactive systems (cf. Section 2). The analysis of emotions can be useful in a later analysis of the socioenactive scenario, identifying which interactions worked to promote well-being among the participants. In this way, the requirement of the Coupling dimension where inputs and outputs are coupled is present, as well as the dynamic system evolution requirement of the Autonomy dimension (cf. Table 1).

The social element in this case would involve bringing together more than one input from different participants generating responses from the environment for each labeled pattern. This is important to meet the requirements of multiple inputs of the Coupling dimension and the requirement for social interactions of the social dimension (cf. Table 1). Other useful inputs that require a parser similar to physiological signals would be the capture of sounds from the environment like clapping, identifying more expressive variations and triggering system responses.

Another important element in a socioenactive system is the integration of computational intelligence into the management algorithm. This is important because it enables the environment responses to the participants to be less programed and linear, adding an important factor in the cycle of socioenative systems, which is social feedback changing the behavior of the system. For this, it is possible to integrate simplified artificial intelligence techniques that use the patterns trained in the classification of signals to generate changes in the environment, such as changes in sound or ambient light (Larradet et al., 2019), or in the devices involved, such as in the robot's behavior. Thus, the system is redefinable by stakeholder, meeting the requirements of the Autonomy dimension and the requirements for environmental data input of the Coupling dimension (cf. Table 1).

The narrative may include a more complex behavior for the robot, which considers the participants' physiological signals, to appear as less trained and closer to something alive. An example for these components could be the narrative of taking a wild animal to a point in the environment with voice commands. In this narrative, physiological inputs such as Heart Rate (HR) could be used by the robot, subtly altering its direction, as well as the audio intensity of the spectating participants, also considering involuntary signals. With this, the system integrates embodied interaction, with the actions of the participants using wearables with the physiological reading sensors, meeting the requirement of the Embodiment dimension. Still, collaborative knowledge construction may emerge from the resolution of group tasks such as taking the robot from one point to another in the scenario, as suggested in the social dimension and in the S1 scenario (Table 1).

Figure 5 shows how the technological communication in this proposed scenario can be constructed where the sensors with physiological reading of the participants dynamically defines a dataset with classified patterns based on the description of the robot's actions and on the labeled signals. These signals would trigger behaviors in the robot and the environment promoting social behavior and generating an ontological description of the system. The focus in this architecture is on the elements of autonomy integrated into the digital dimension. The parser process will receive the raw signals and classify them using Machine learning (ML) to label the significant changes in signals by triggering responses through the robot and environment elements.

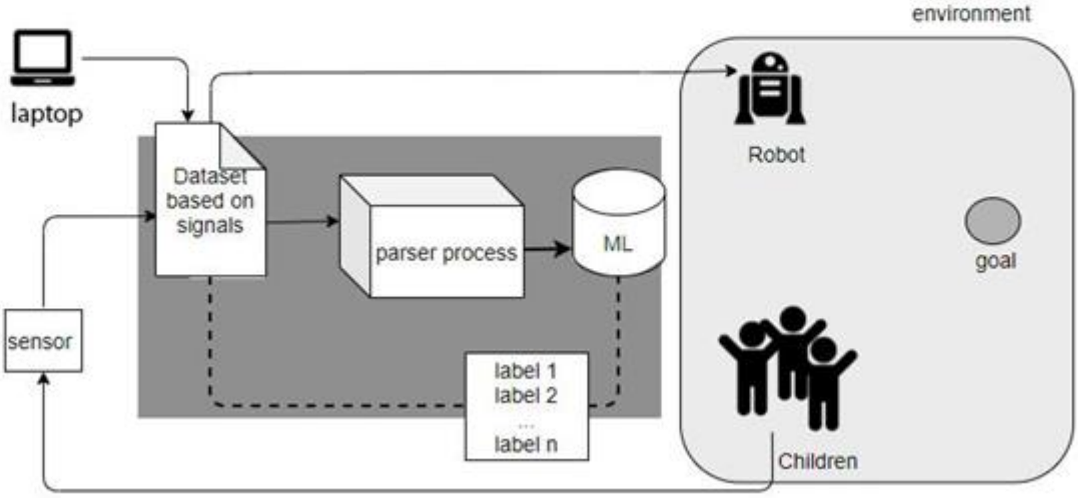

Figure 5. socioenactive system based on physiological sensors with integrated computational intelligence.

For the parser system of the physiological readings, data processing is necessary first, which serves to resize the dataset where the information from the readers or other relevant stakeholder data is stored. Commonly, the time series of sensors such as HR and GSR return lists of numerical vectors corresponding to the frequencies associated with a time value referring to the sequential position of the data. If there is any data other than those returned by the sensors, such as user id, or some descriptive value important to the system, the reduction of attributes can be done using algorithms such as Principal Components Analysis. The stored data, in this case, is converted in a standardized way organized in a simplified sequence of values.

Once the input data has been redimensioned, a characteristic of a socioenative system is the use of multiple physiological inputs, as inputs from more than one person. These inputs can define a merged mapped pattern that can generate an environment response such as commands in mBot behavior.

Also, performing automatic emotion recognition in at least one of the children can indicate whether the workshop is positively affecting him-her. The classification of emotions can be used for further analysis, as important information regarding how activities and interactions influenced the participants' well-being.

Finally, changes in the environment can be activated as actions to respond to user inputs, such as changes in background music or ambient lighting. Changes in ambient lighting, for example, can influence emotional expressiveness and cognitive performance (De Ruyter & Dantzig, 2019), as well as changes in ambient music can influence the emotional state or engagement of the participants (Thomas et al., 2017). These triggers associated with the input patterns, can also be mapped as direct commands to mBot, that could be executed from patterns read from physiological sensors.

This proposal of S3 meets the dimensions where S1 and S2 presented weaker results, as pointed out by Figure 4, in the dimensions of Coupling and Autonomy, resulting in a direct evolution of the S1 and S2 design complementing the requirements of a Socioenative system construction integrating the user feedback cycle through physiological inputs and dynamic system actions based on these inputs.

4.2 Preliminary Results of the S3 System Simulation

Considering preliminary testing based on the S3 proposal, a simulation was developed, considering generation of the inputs of untreated physiological data and classifying them as outputs for the mBot and the system manager. This simulation aims to implement part of the system communication proposed by the architecture presented in Section 4.1, serving as an initial result for the logical system that can be applied to socioenactive scenarios for educational contexts.

The simulation was built using the Linux environment and the Python programming language, as well as libraries for hardware events and machine learning packages. The next experiments still suggest mBot responses that can be implemented using the Scratch language. Elements such as environment outputs, robot actions using sensors, or real time behavior tracking and classification were not included in this simulation since they require a pilot experiment in a real scenario. Thus, the experiments in this section focus on the logical process that involves the dimensions of the system's autonomy with the integration of an input processing that simulates physiologically reading data from the coupling dimension.

An algorithm was implemented that sequentially generates numerical lists with a structure similar to HR readings, which are sent as a running signal and converted into keyboard events using the Pynput library[2], responsible for mapping keyboard outputs. The parser of these data is simple, and it is only necessary to calculate more significant variations in predefined timestamp intervals. This protocol should be built along with a workshop narrative that would define activities for the glove of users that could stimulate changes in HR readings. A similar process can be used to read and process information from the environment, such as children's claps, that generate numerical lists with varying intensities.

With these variations in the HR inputs, mBot commands can be triggered, using keyboard mapping. These keyboard commands are fundamental to creating dynamic responses in mBot, since actions can be mapped with triggers for keyboard commands. In this way, the readings can generate commands for the robot, which will go through a classification of patterns in order to associate variations of social behavior with actions of the robot. These interactions are part of the proposed user feedback cycle where people change the behavior of the system, which dynamically also affects people's behavior.

Thus, physiological signals data are dynamically stored that trigger commands on the keyboard that can be mapped as mBot actions. These actions can be subtle behaviors such as changes in the direction in which the robot walks, giving a more lively and unpredictable aspect to the artifact, which combined with the narrative, encourages new reactions from the children who participate in a workshop that implements this strategy.

In addition to the simulated HR sensor signals, an emotion recognition process was tested based on the Support Vector Machine (SVM) pattern recognition algorithm that classifies the basic emotions, based on the technique presented in (Gonçalves et al., 2017). This technique uses facial feature tracking for landmarks extracted from a bounding box referring to user faces using Local Binary Pattern (LBP) and Principal Components Analysis (PCA). Figure 6 shows the parser process used in the simulation where the data generated by simulating an HR sensor are treated and classified in order to generate behavioral outputs for the robot.

[2] Moses Palmér. (2021). Pynput [Online]. Available at: https://www.https://pypi.org/project/pynput/ (Accessed: 11 April 2021).

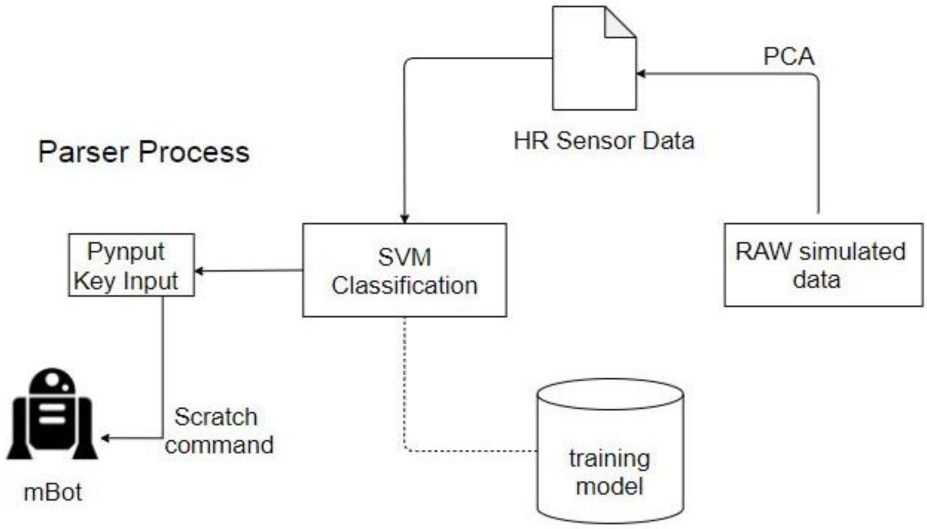

Figure 6. Parser process of simulated physiological data.

The technique uses facial action units (AUs) that track landmarks using a calculation based on POI (Points of Interest) displacement and a facial expression analysis, focusing on recognizing emotional states as happy, angry, fear, sadness, disgust and surprise. Figure 7 presents an example of the result obtained by applying the algorithm to recorded videos from S2 workshop, where we can observe the automatic recognition of emotion after tracking and identifying the face of one or more children. This process could be applied with a webcam as an input, following protocols that frame the face of at least one child. This type of algorithm is especially useful for further analysis, due to its high computational cost in training and classification, such as neutral, happy, sad, fearful, etc.

Figure 7. SVM-based automatic emotion recognition algorithm and landmark tracking by facial units applied to an educational environment video.

As data read directly from sensors such as HR and GSR, facial expressions are considered involuntary data, which can be used as a behavioral pattern to trigger changes in the environment or in the robot, making the system experience more enactive. With the HR signals and an automatic emotion classification process, the system has multiple inputs and different patterns, which offer several possibilities to build outputs based on user data. The environment light could, for example, change depending on the classified emotions of the children, and simultaneously the robot could trigger actions based on more significant changes in the HR signals.

The system can consider reading more than one file referring to an HR sensor, for example, or combining other input patterns, such as clap sounds. As artifacts, low-cost sensors can be used in order to change the environment; for example, iterating the ambient music depending on the input classifications, or activating a color sensor controlled by an Arduino. So, through the narrative and outputs present in the experience, new behaviors may emerge from people, promoted by group task resolution. The system then receives numerical readings similar to values from a simple HR sensor, classifying the patterns by identifying more significant variations that trigger behaviors in the robot. In parallel, the system can classify the emotions of one child, which triggers changes in the environment. With this process, the system's autonomy is present with the automatic classification process using machine learning and the coupling is strong since the inputs are based directly on the users' actions and behaviors.

4.3 A Narrative proposal for S3 based scenario

A scenario based on S3 can be implemented with different types of narrative for socioenactive systems, since the inputs and outputs contemplate the entire expected user feedback cycle. This section presents a succinct example of a narrative that could be integrated into a S3-based workshop.

Considering that the focus of the S1 and S2 workshops was designing environments for children, the narratives consider playful elements and integrated wearables and ubiquitous technologies in fun tasks that foster social interaction.

In this way, the mBot could represent a wild animal, such as a rabbit, in a task of taking the animal to a point in the scenery, which would represent a safe area. The physiological sensors of HR or ECG could be integrated in children in the four corners of the scene, with gloves that attract the rabbit, depending on the child's excitement. The interaction actually causes the patterns read to indicate changes in breathing or heart-beats and to indicate which corner the mBot should turn to.

Another group of children can wear boots that direct the rabbit elsewhere. These boots would be coupled with presence sensors that would indicate changes in direction to the mBot, also considering the influence of other children with the embedded gloves with HR or ECG sensors.

This dynamic would promote social interactions and group work, since the children must act together, both the group within the arena with mBot and the group in the audience, with the gloves. Still, the sensors can generate behaviors in mBot, making the system responsive to social behavior. Readings and classifications of children's emotions will indicate to the system the changes in feelings, which, associated with the interactions, will indicate to the system that mBot behaviors are improving fun and can adapt these behaviors to be more frequent, for example.

With these interactions, the entire enaction cycle will be present in the workshop that uses and evolves the concepts used in S1 and S2, making S3 a complete socioenactive system. Figure 8 shows the elements in the dimensions: **Physical** as the mBot (a), safe area (b), gloves (c), boots (d), physiological sensor (f) and environment effect (j); **Digital** as the laptop (g); **Social** as children (e), researchers (h) and children’s teachers (i).

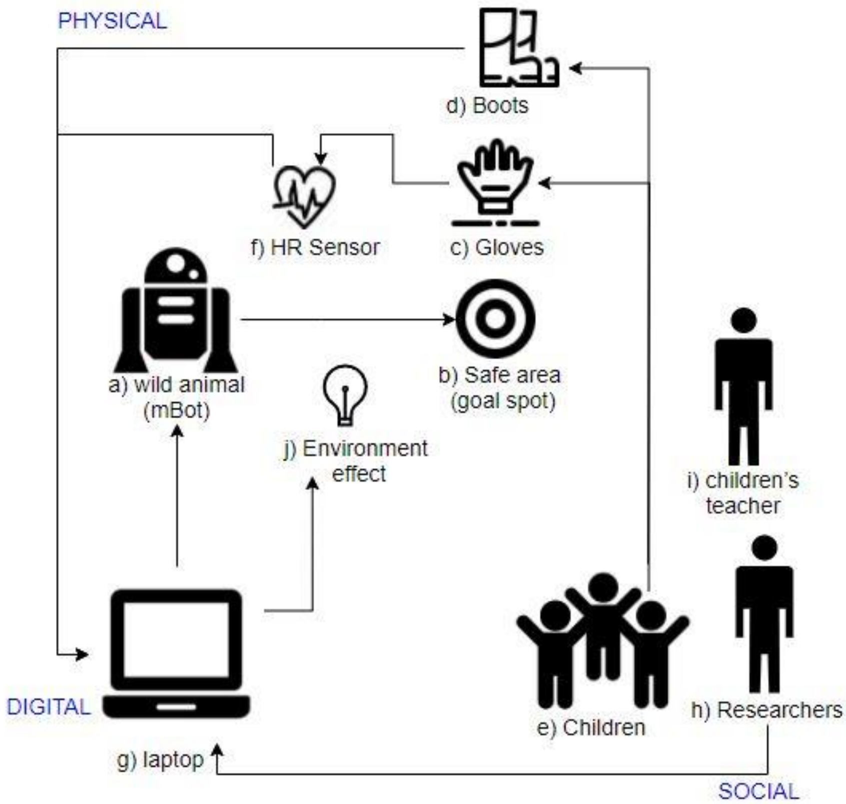

Figure 8. Elements and dynamic of the proposed system S3.

In future work, a pilot should test the narrative and these logic elements with sensors and physical artifacts in order to identify the efficiency and feasibility of a workshop following this model.

5. Discussion

This work proposes a workshop design for a socioenactive system that meets all the guidelines and dimensions expected in the recent literature. The presented architecture advances the concepts for complete enative systems predicted by Rodríguez et al. (Rodriguéz et al., 2014) and Baranauskas (Baranauskas, 2015) representing a next step in socioenactive systems for educational environments. The S3 model offers all the technological structure necessary for the feedback cycle of the Social-Digital-Physical dimensions present in socioenactive systems.

In order to propose a solution for the socioenactive system gaps applied to educational environments, this work introduces the implementation of AI and embedded sensors that allow the feedback loop between the human and technological aspects expected in an enactive interaction. The signals captured from the physiological reading sensors allow the definition of a database or rule set to support the generation of behavior in real time, making the experience emerging from this scenario enactive, and responding to guidelines G1 and G2 (cf. section 2).

The extracted patterns of the participants' behavior, which might have labels extracted from physiological sensors, or the automatic recognition of emotions, categorize the definition of technologies supported by sensors to detect and track participants behavior (G2).

These captured and treated patterns, usually analogue, are identified by their variations and generally indicate the physical stakeholder actions, ranging from commands to the mBot or gestures. Likewise, automatic emotion recognition, with CNN applied to 3D masks, is an indication of which children are having fun, serving as a response for mBot triggers that motivate group work and encourage everyone to participate in the task.

With a narrative that promotes group actions and an ontological description that unites the narrative with the technological systems involved, it is possible to create a mapping between psycho-physiological dimensions of content, responding to guidelines G3 and G4. In the proposed workshop design, multiple interactions can be used as inputs, such as physiological readings referring to the recognition of emotions or direct readings such as heartbeat, triggering actions in the robot or environment. Pedagogical elements inserted in the narrative that justify the resolution of group tasks must support physical-virtual based activities and interactions.

In this way, the proposed technological structure has interaction between the Physical, Digital and Social dimensions: the participants interact with each other through coordinated actions, and with the system through the scenario objects (e.g., the gloves, the boots); reading of physiological data is taken by the system which processes input data directing new actions through its digital and physical outputs, on the robot. Also, interactions between the participating children and the artifacts trigger new actions and feelings in the social dimension.

Following the SEES framework, it is possible to point out all model steps suggested by the model: the learning objective of S1 evolves through the resolution of group tasks based on the new narrative; the pedagogical methodology/practice will be present in the proposal of S3 that integrates a playful narrative that will be built together with the teaching staff responsible for the children’s education; in the same way, activities for target audience follows the same educational context environment to which S1 and S2 were applied; social behavior is present in the whole experience, which promotes the solution of tasks in group; the environment is enactive since it comprises the entire feedback loop with the user where the system and people affect and are affected by the interactions; physical-virtual setting, is as proposed in the architecture of section 3.2; interactions are provided by the artifacts proposed and their coupled outputs and inputs, as well as the emerging social interactions among the group; multimedia content are proposed in the Digital layer of S3; physical-virtual environment are as proposed in section 3.2, where the scenario and the artifacts are integrated in a dynamic social environment that unites the Social, Digital and Physical dimensions.

The use of machine learning for facial expression classification can incorporate ontological changes in the system's behavior that fine-tune the parameters of mBot actions according to participant behavior. Still, the use of sensors incorporates social layer patterns that feed the dataset for system behaviors according to people's actions. These characteristics guarantee the system's socioenactivity.

This socioenactive system design is redefinable by stakeholder since there are software changes in the system execution that will be based on intelligently processed physiological inputs. The feedback cycle, input and output coupled, that affects system and people behavior, will happen through sensors integrated into wearables (HR integrated into gloves, for example) and the interactions.

The main contribution of this work is the proposal of an S3 system that refines socioenative systems presented in recent literature with the potential to promote a collective knowledge construction through the resolution of group tasks using embodied interaction, which might lead to learning and cognition through action. The features incorporated in S3 allow participants' interactions, through artificial intelligence and pattern recognition, to affect the sensory responses of the environment such as messages embedded in artifacts, changes in ambient outputs such as lighting and sound, and especially changes in robot actions and the system. It is expected to build, in future works, workshops based on the S3 architecture where emerging social aspects can be observed and their impact on real educational environments evaluated.

6. Conclusion

This work analyzed socioenactive systems in the recent literature, identifying requirements that allow evolving the concepts of system autonomy and users coupling, in order to define a system that fills the lack of a complete cycle of socioenactive system, illustrated in the educational environment. These results point to a model for building a socioenactive system based on group task resolution, which promotes learning through actions and considers, through artificial intelligence and pervasive sensors, a dynamic behavior of the system based on the social dimension. This proposal considers physiological inputs and transforms them into dynamic responses of the system, applied to interactions that promote the social side of experiences with mBot, for children in an educational environment.

A simulation of part of the proposed S3 system was presented, where the model of inputs and interactions with the user is considered through data of physiological reading, classification of emotions, and evolution of interaction models used in recent socioenactive systems. The method of automatic emotion classification can point out further analysis as socioenactive systems can positively affect the emotional state through social experiences. The simulation shows how the proposed architecture can be implemented, using a succinct narrative presented.

The S3 promotes children's high degree of embodied peer collaboration and initiative to accomplish the tasks through the full cycle of enactive physical/social feedback. These results contribute to inform the design and construction of future socioenactive systems.

As further work, the proposed system can be put into action in a real scenario to promote social interactions, to solve tasks in an educational environment, and to create conditions for learning with experience of interacting with mBot and the other elements. Still, other narratives can use the proposed S3 system generating different socioenactive experiences.

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Compliance with Ethical Standards

This section presents information regarding statements on open data, ethics, and conflict of interest. In this study, all parents signed a Term of Consent, allowing their children to participate in the study, and all children expressed their consent as well. The research was approved by the University of Campinas review from Ethics Committee, under number CAAE 72413817.3.0000.5404. The authors do not wish to declare any conflict of interest.

References

Adams-Labonte, S. K. (2012). *Daytime impairment due to college students' technology use during sleep: Similarities to sleep apnea*. [Poster presentation]. Meeting of the American Psychological Association, Orlando, FL. [GS Search]

Baranauskas, M. C. C. (2015). Socio-enactive systems: Investigating New Dimensions in the Design of Interaction Mediated by Information and Communication Technologies, FAPESP Thematic Research Project #2015/16528-0. [GS Search]

Baranauskas, M. C. C., Martins, M., & Valente, J. A. (2013). *Codesign de redes digitais: tecnologia e educação a serviço da inclusão social*. Porto Alegre: Penso, 2013. 304 p. ISBN 9788565848633. Número de chamada: 371.3078 C669. [GS Search]

Baranauskas, M. C. C., Mendoza, Y. L. M., & Duarte, E. F. (2021). Designing for a socioenactive experience: A case study in an educational workshop on deep time. *International Journal of Child-Computer Interaction*, *29*, 100287. doi: 10.1016/j.ijcci.2021.100287 [GS Search]

Brady, K., Gwon, Y., Khorrami, P., Godoy, E., Campbell, Dagli, W. C., & Huang, T. S. (2016). Multi-Modal Audio, Video and Physiological Sensor Learning for Continuous Emotion Prediction. In *Proceedings of the 6th International Workshop on Audio/Visual Emotion Challenge (AVEC'16)* (pp. 97–104). ACM: New York, NY, USA. doi: 10.1145/2988257.2988264 [GS Search]

Brochado, R. A., & Carvalho, M. A. G. (2021). Revisão sistemática de estudos e aplicações de modelos pedagógicos diversificados. *Revista Brasileira de Informática na Educação*, *29*, 718-745. ISSN 2317-6121. doi: 10.5753/rbie.2021.29.0.718 [GS Search]

Caceffo, R. Alves, E., Bonacin, R., dos Reis, J., Carbajal, M., D'Abreu, J. V., Brennand, C., Lombello, L., Valente, J. A., & Baranauskas, M. C. C. (2019). Collaborative Meaning Construction in socioenactive systems: Study with the mBot. In P. Zaphiris, A. Ioannou (eds.), *Learning and Collaboration Technologies. Designing Learning Experiences*. HCII 2019. Lecture Notes in Computer Science, vol 11590. Springer, Cham. doi: 10.1007/978-3-030-21814-0_18 [GS Search]

De Ruyter, B., & Van Dantzig, S. (2019). Ambient Lighting Atmospheres for Influencing Emotional Expressiveness and Cognitive Performance. In: I. Chatzigiannakis, B. De Ruyter, I. Mavrommati (eds.), *Ambient Intelligence. AmI 2019.* Lecture Notes in Computer Science, vol 11912. Springer, Cham. doi: 10.1007/978-3-030-34255-5_1 [GS Search]

Fortenbacher, A., Niels P., & Haeseon Y. (2017). [LISA] learning analytics for sensor-based adaptive learning. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference (LAK'17)* (pp. 592-593). ACM: New York, NY, USA. doi: 10.1145/3027385.3029476 [GS Search]

Gonçalves, D. A., Todt, E., & Cláudio, D. P. (2017). Landmark-based Facial Expression Parametrization for Sign Languages Avatar Animation. In *Proceedings of the XVI Brazilian Symposium on Human Factors in Computing systems (IHC 2017)* (pp. 1–6), Article 34. ACM: New York, NY, USA. doi: 10.1145/3160504.3160507 [GS Search]

Imamura, R. E. M., & Baranauskas, M. C. C. (2019). A framework for socio-enactive educational systems: linking learning, design, and technology. In *Proceedings of the 18th Brazilian Symposium on Human Factors in Computing systems (IHC'19)* (pp. 1-11), Article 1. ACM: New York, NY, USA. DOI:10.1145/3357155.3358443 [GS Search]

Jiménez, R., María, R., & Merino, S. (2017). Enactive and Embodied Learning In Higher Education. *Functional Neurology, Rehabilitation, and Ergonomics*, *7*(45). [GS Search]

Kaipainen, M., Normak, P., Niglas, K., Kippar, J., & Laanpere, M. (2008). Soft ontologies, spatial representations and multi-perspective explorability. *Expert systems, 25*(5), 474–483. [GS Search]

Kaipainen, M., Ravaja, N., Tikka, P., Vuori, R., Pugliese, R., Rapino, M., & Takala, T. (2011). Enactive systems and enactive media: Embodied human-machine coupling beyond interfaces. *Leonardo*, *44*(5), 433–438. [GS Search]

Larradet, F., Niewiadomski, R., Barresi, G., & Mattos, L. (2019). Appraisal theory-based mobile app for physiological data collection and labelling in the wild. In *Adjunct Proceedings of the 2019 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2019 ACM International Symposium on Wearable Computers (UbiComp/ISWC '19 Adjunct)* (pp. 752–756). ACM: New York, NY, USA. doi: 10.1145/3341162.3345595 [GS Search]

Lazar, J. et al. (2017). *Research Methods in Human Computer Interaction*, Morgan Kaufmann, 2017. [GS Search]

Lugmayr, A., & Stuart B. (2016). Free UX Testing Tool: The LudoVico UX Machine for Physiological Sensor Data Recording, Analysis, and Visualization for User Experience Design Experiments. In *Proceedings of the SEACHI 2016 on Smart Cities for Better Living with HCI and UX (SEACHI 2016)* (pp. 36-41). ACM: New York, NY, USA. doi: 10.1145/2898365.2899801 [GS Search]

Maturana, H. R., & Varela, F. J. (1992). *"Afterword". The tree of knowledge: the biological roots of human understanding (Revised ed.).* Shambhala Publications Inc. p. 255. ISBN 978-0877736424. [GS Search]

Rahim, A., Sagheer, A., Nadeem, K., Dar, M. N., Rahim, A., & Akram, U. (2019). Emotion Charting Using Real-time Monitoring of Physiological Signals. In *2019 International Conference on Robotics and Automation in Industry (ICRAI)* (pp. 1-5), Rawalpindi, Pakistan, 2019. doi: 10.1109/ICRAI47710.2019.8967398 [GS Search]

Rodríguez, A., López, P. G., & Rossi., G. (2014). Sketching for designing enactive interactions. In *Proceedings of the XV International Conference on Human Computer Interaction (Interacción'14)* (pp. 1–2), Article 39. ACM: New York, NY, USA. doi: 10.1145/2662253.2662292 [GS Search]

Röggla, T., Najereh S., Zhiyuan Z., Alice P., & Pablo C. (2017). Enhancing Music Events Using Physiological Sensor Data. In *Proceedings of the 25th ACM international conference on Multimedia (MM'17)* (pp. 1239–1240). ACM: New York, NY, USA. doi: 10.1145/3123266.3127919 [GS Search]

Sichao, S., & Seiji, Y. (2018). Designing Expressive Lights and In-Situ Motions for Robots to Express Emotions. In *Proceedings of the 6th International Conference on Human-Agent Interaction (HAI'18)* (pp. 222–228). ACM: New York, NY, USA. doi: 10.1145/3284432.3284458 [GS Search]

Stamper, R., Liu K., Hafkamp, M., & Ades, Y. (2000). Understanding the roles of signs and norms in organizations-a semiotic approach to information systems design, *Behaviour & Information Technology*, *19*(1), 15-27. doi: 10.1080/014492900118768 [GS Search]

Sun, M., Leite, I., Lehman, J. F., & Li, B. (2017). Collaborative storytelling between robot and child: A feasibility study. In *Proceedings of the 2017 Conference on Interaction Design and*

Children (IDC'17) (pp. 205–214). ACM: New York, NY, USA. doi: 10.1145/3078072.3079714 [GS Search]

Valente, J. A., Caceffo, R., Bonacin, R., Gonçalves, D. A., Reis, J. C., & Baranauskas, M. C. C. (2021). Embodied-based Environment for Kindergarten Children: revisiting constructionist ideas. *Accepted for publication in British Journal of Educational Technology*, *52*, 3. [GS Search]

Valente J. A., Caceffo, R., Moreira, E. A., Bonacin, R., Reis, J. C., Carbajal, M. L., D'abreu, J. V. V., Gonçalves, F. M., Brennand, C. V. L. T., & Baranauskas, M. C. C. (2020). A Robot-based Activity for Kindergarten Children: an embodied exercise. In *Proceedings of Constructionism Conference 2020* (pp. 137-146), Dublin. ISBN: 978-1-911566-09-0. [GS Search]

Varela, F. J., Thompson, E., & Rosch, E. (1992). *The embodied mind: Cognitive science and human experience*. MIT Press. p. 9. ISBN 978-0262261234. [GS Search]

Wang, C., Röggla, T., & César, P. C. (2015). Analysing Audience Response to Performing Events: A Web Platform for Interactive Exploration of Physiological Sensor Data. In *Proceedings of the 23rd ACM international conference on Multimedia (MM '15)* (pp. 749–750). ACM: New York, NY, USA. doi: 10.1145/2733373.2807976 [GS Search]

Weiser, M. (1999). The computer for the 21st century. *SIGMOBILE Mob. Comput. Commun. Rev. 3*(3), 3–11. doi: 10.1145/329124.329126 [GS Search]