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A Prototype Implementation of a Virtual Platform with Robotic Integration and Machine Learning Capabilities for the Execution of Cognitive Psychology Experiments in Children

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Abstract

Virtual platforms and autonomous robotic systems have recently gained a lot of attention due to the enormous growth of novel computational techniques, such as artificial intelligence and machine learning, allowing various fields and processes to be transformed. Cognitive psychology is a field where such virtual platforms can be applied in order to enhance the current procedures and processes, offering an objective and non-intrusive method, for psychological tasks execution, especially in the case of children. More specifically, this paper presents a virtual platform, complemented with a robotic experimenter and a machine learning processing module, allowing the objective and neutral execution of psychological experiments and tasks to children, remotely or in person.

Keywords: Socially assistive robotics, intelligent robots, cognitive psychology, virtual learning platform, cognitive development, experiment execution, piaget conservation tasks, open research data, machine learning

1. Introduction

Virtualization has become more common in recent generations as open participation in the digital revolution has risen (Huamaní, 2014). Virtual applications for developmental study with children, on the other hand, have gotten very little consideration and the methods used to execute such cognitive developmental studies are still lacking the inclusion of technology, such as the use of virtual and automated platforms or even the inclusion of automated robots.

As the COVID-19 outbreak diminished social interaction, leading to the closure of many developing institution research facilities in 2020, scientists started to look for alternative ways of executing cognitive development experiments, among which the use of virtual research techniques is the most promising one (Gijbels et al., 2021), since it allows the execution of psychological experiments without requiring a direct social interaction and at the same time the participants are not influenced by the physical presence of the experimenter, which could affect negatively their behavior.

Considering this digital transition, the shift from in-person to virtual research is particularly challenging and recent research studying manipulation, proposed even tools of detecting manipulators among digital platforms users (Fedushko, Kolos, & Malynovska, 2019). This scientific challenge concerns also developmental psychologists due to lack of equipment used for recording critical aspects of experiments. Acknowledging this, researchers want to contribute to the field by providing tools that enable performing different and regulated virtual cognitive development experiments in children.

However, in order for these regulated virtual cognitive experiments to be executed and delivered to children, novel and sophisticated virtual platforms are required, which will be capable of parametrizing the experiment structure, e.g. its questions, answers and interface, while also providing innovative ways of interaction between the experimenter and the children, realizing the gamification of the whole process, attracting children's interest and therefore optimizing the process by obtaining the best possible results. Such virtual learning/experimentation platforms are extensively described and presented in the literature (e.g Bri et al., 2009; Georgouli, 2011; Kliziene et al., 2021), but they are not customizable enough and most of them are outdated and they do not integrate modern technologies, like automated humanoid robots and machine learning.

Towards this direction, the authors were motivated to design and implement a novel virtual platform that can host different experiments, it is extensible and combines the use of an automated robot in the role of the experimenter (Dautenhahn, 1999; Feil-Seifer & Mataric, 2005; Nourbakhsh & Dautenhahn, 2003) in order to offer the children participants not only an easy way of interacting with the questions, but also an innovative gamified environment by using a robot (Wei et al., 2011), which transforms a currently traditional process to an interesting and unique experience. The aforementioned platform also has machine learning capabilities and it can automatically analyze the results of the experiments that are performed through it (Jacobucci & Grimm, 2020). The scope of this research is to describe in detail the design architecture and the implementation details of this virtual platform and perform a basic functionality test, by using three different modes of execution in a proof-of-concept experiment to showcase the possible use cases of the virtual platform. The experiment chosen is based on Piaget's conservation tasks, which is among the most popular experiments in cognitive development area. The scientific hypothesis concerning the high functionality of the virtual platform was formulated. The virtual platform is expected to reach 100% success rate in executing the experiments and storing results in the database and at the same time provide the users with a smooth and enjoyable experience. At the same time the results of the chosen experiment will be presented and analyzed in order to further reinforce and empower the significance and importance of the virtual platform in the area of modern psychology experimentation and measurement.

The rest of the paper is organized as follows: The background section discusses the use of virtual platforms in psychology, briefly presents Piaget conversational tasks theory, analyzes why the inclusion of a robotic experimenter is in favor and provides a brief overview of machine learning in psychology. Then, the prototype implementation of the proposed virtual platform is presented in detail, showing its advantages in configurability and adaptability. Finally, the execution of Piaget's experiments is used as an example of the virtual platform usage in cognitive developmental and the experimental methodology and results are presented and discussed.

2. Background

This section provides a literature review to each respective background related to the topic of this paper.

2.1 Virtual Platforms in Psychology

The fact that experimental methods involving children are often more complicated than those involving adults is undoubtedly among the main factors for the sluggish adoption of virtual research in future developments. Considering age-specific visual attention, one of the biggest challenges for early childhood, developmental specialists are figuring out how to engage individuals, reduce distractions, and incentivize involvement effectively. Relationship between even a patient and a therapist might aid in keeping the child's attention (Gijbels et al., 2021). Even though the job is automated, formative research investigations, particularly those focusing on audio or visual processing, might gain from collected data (Adams et al., 2018). In a controlled meeting, the researcher-observer can note any situations or challenges that arise and adapt as required.

Face-to-face contacts have historically been used when participating in research environments. Although interpersonal relations over a screen are generally regarded as "obliterated" and cannot entirely substitute in-person encounters, executing virtual experiments facilitate remote execution, thus providing ease of access and improving participation and involvement (Naseer et al., 2019). Furthermore, the simultaneous entrance of a foreigner, such as a researcher, and a new location, such as the facility, in the experimental process might conflict with the integrity of collecting data in research related to children. Virtual platforms eliminate those new variables by enabling the child to interact with a machine in the comfort of its own environment, thus mitigating the aforementioned risks.

2.2 The Need for a Robotic Experimenter

With robots, children, especially those with Autistic Spectrum Disorder (ASD), demonstrate enhanced social skills, as evidenced by increased emulation and collaborative concentration. One of the most important features of using robotics with children is to keep them engaged in extended sessions (Michaud et al., 2007) and therefore keeping their attention focused on particular social skills (Prescott & Robillard, 2021). One of the reasons why children like interacting with robotics is that such agents are basic in look and conduct, straightforward, and not as daunting as people may be in high social complexity (Marchetti et al., 2022). The research on Social Assistive Robots (SAR) psychotherapy for children, especially those with ASD, is vast and it helps researchers classify trials based on the type of robotics utilized and the interactions that are happening. Considering these, the virtual platform could enable researchers to expand the research with experiments in children beyond those with ASD.

Researchers believe robotics may induce observable behavioral reactions to stimulations and create the same stimulation for diverse participants (Prescott & Robillard, 2021). Nevertheless, among the most significant inherent disadvantages of utilizing a robot to diagnose, is the lack of fundamental nursing sensibility in everyday clinical practice. It is important to note that robots might aid in collecting quantitative measurements of children. In the long term, the robot's activities might be converted into quantifiable measurements that might be used for further analysis.

In principle, empirical research shows that using robots with children has beneficial outcomes. Irrespective of the sort of robots utilized, researchers discovered that such gadgets could be helpful as mediating devices throughout unpleasant therapies or merely during a child's hospitalization (Marchetti et al., 2022). Furthermore, such studies reveal that robots benefit children and caretakers by reducing parental worry and assisting professionals during certain operations (Pivetti et al., 2020). However, as previously stated, these findings have drawbacks, the most significant of which are the limited number of persons, the cultural differences, the varied robot characteristics, and the aging nonuniformity, all of which will have to be considered in a forthcoming related study. Most of the drawbacks are addressed in the virtual platform presented here by providing an open and online platform that has interfaces and the ability to support multiple remote controlled robotic experimenters.

According to literature, there are two general types of SARs (Feil-Seifer & Matarić, 2005): non-humanoid and humanoid. In this paper, only humanoid robots are considered, since they are beneficial not only for movement therapy but also for their pleasant interpersonal characteristics (Marchetti et al., 2022). Moreover, humanoid robots with limbs, arms, feet, and heads enable broader interaction and improve children's motivation due to the innately social and educational character, as highlighted by numerous researchers. Studies on cognitive development pointed out the role of robots in transmission of social cues (Masson et al., 2017) as well as in children's general learning ability (Jamet et al., 2018).

2.3 Machine Learning in Psychology

Machine learning is increasingly being applied in psychology to understand and improve human learning and cognition. Researchers are using machine learning to study brain activation patterns related to learning scientific concepts, providing insights into how the brain learns abstract concepts (Mason & Just, 2016). Additionally, artificial neural networks are employed in order to help psychologists and teachers understand developmental stages, identify students with dyslexia and other learning difficulties and tailor educational interventions (Sailer et al., 2023). It has also been used to analyze eye-tracking data for understanding reading comprehension and mind-wandering (D'Mello et al., 2020). Moreover, it is being utilized to predict mental health problems, such as loneliness, depression, and anxiety, by analyzing psychological and sociodemographic traits (Altschul et al., 2021). All those use cases suggest that the general trend in the field indicates that machine learning is increasingly being applied and it can provide innovative ideas that may have taken considerable time for humans, in part because it is less constrained by limits on available knowledge and biases (Bartlett et al., 2023). Such research typically involves analyzing behavioral data, speech patterns, or even physiological signals to gain insights into the cognitive and emotional development of children.

However, concerns about machine learning techniques are mainly about the "black box" results they produce (Elhai & Montag, 2020; Guidotti et al., 2018). The learning algorithms can predict outcomes successfully with great accuracy, but they do not provide the causal or explanatory information that traditional methods generate and require. This is not essentially bad in psychology as contemporary researchers have argued that: "psychology's near-total focus on explaining the causes of behavior has led much of the field to be populated by research programs that provide intricate theories of psychological mechanism, but that have little (or unknown) ability to predict future behaviors with any appreciable accuracy" (Yarkoni & Westfall, 2017). Moreover, beyond prediction, machine learning and big data will enable social scientists to chart new territory in exploring psychological phenomena as human behavior is very complex and the variables influencing it are still only partially explored and understood.

3. A Prototype Implementation of Virtual Experimentation Platform with Robotic Experimenter

The virtual experimentation platform is built using various web technologies, which are interconnected to achieve a complete and successful result. The online platform operates via the Internet, as shown in Figure 1. The main program runs on the server and there is direct connection to the database, which is also hosted on the server. Users access the platform through their preferred web browser over https protocol.

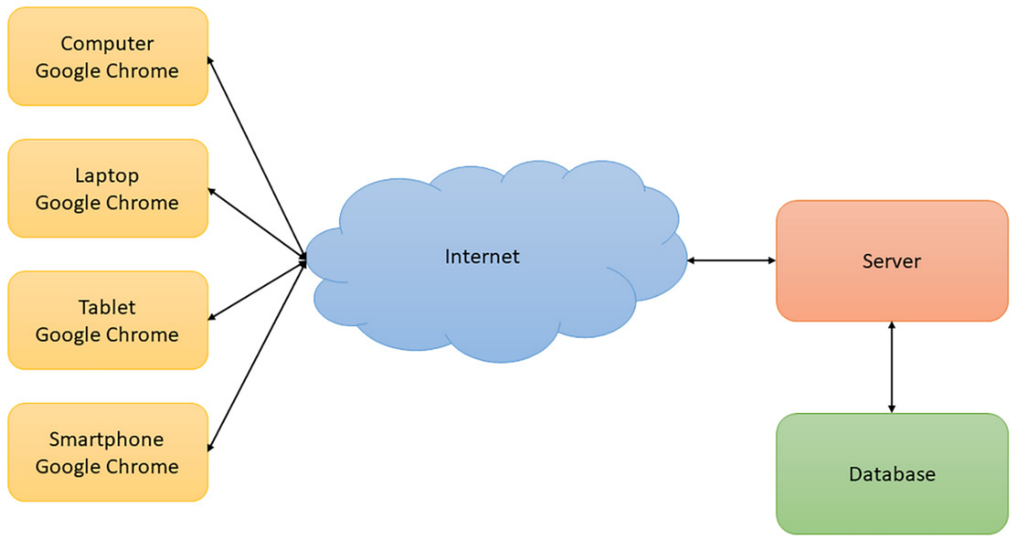

Figure 1. Virtual experimentation platform architecture

The Apache Web Server is used for serving the virtual experimentation platform, which allows multiple users to access the online platform at the same time. The technologies used to build the core of the virtual platform are HTML5, CSS3, JavaScript and PHP. For the connection with the robotic experimenter and the machine learning module, the programming language Python was also used. The program is divided into separate components that operate together and communicate with each other. These components are shown in Figure 2. and will be analyzed in detail below. This initial prototype version of the virtual experimentation platform is localized only in the Greek language (as a consequent, examples in some figures below are in Greek language). Support for multiple languages is planned and it can be easily extended and supported in future versions.

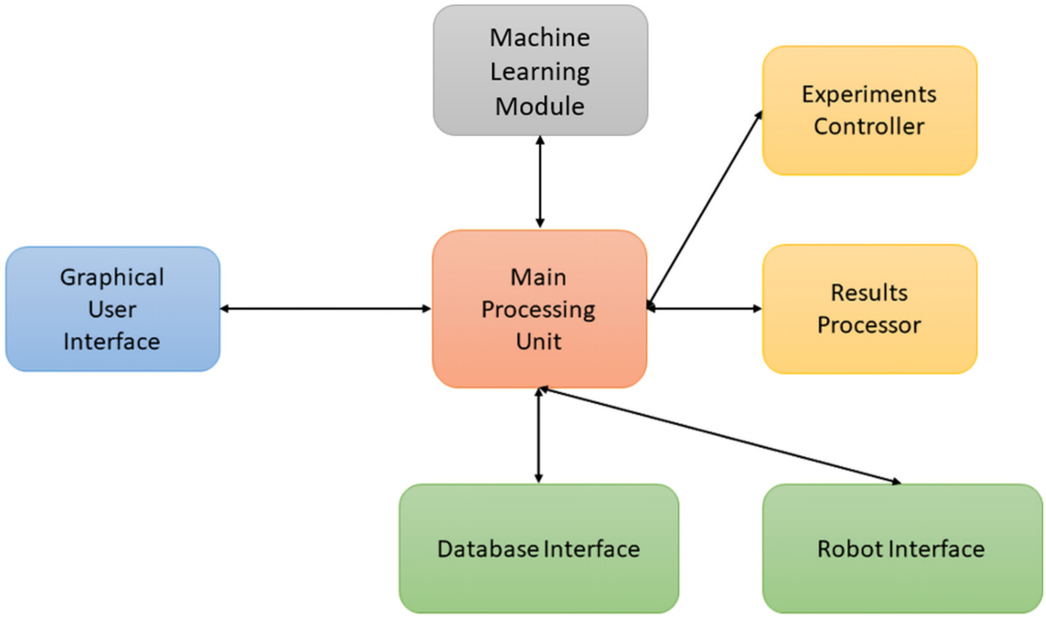

Figure 2. Core components of the program of the virtual experimentation platform

3.1 Main Processing Unit

The main processing unit of the virtual experimentation platform is the brain of the whole system which receives information from all the other components and determines which processes need to be executed. The most frequent interaction happens with the graphical user interface, as it receives all the necessary commands from there. Then according to these commands, it communicates with the rest of the components and sends back to the graphical user interface all the necessary information to be displayed on the users' screens.

3.2 Graphical User Interface

The graphical user interface is the environment that the user interacts with, in order to be able to use the virtual experimentation platform. Principles and techniques of modern software engineering and human computer interaction (HCI) were used to design and create the user experience (UX) (Machado & Tao, 2007; Alomari et al., 2020). The user interface is simple, but functional, without unnecessary buttons that could confuse the user. Also, the buttons and the information given to the user are placed in a manner that they are easily visible and clear.

The entire graphical interface follows the same design principles and it can be adjusted automatically depending on screen size and device type. All types of modern devices are supported, such as personal computers, laptops, tablets and smartphones. On large screens, the content is displayed as a whole throughout the screen, while on small screens the content components are automatically aligned one below the other and they are easily accessible by the user with the help of a scrollbar.

Finally, the online platform is compatible with all modern web browsers, namely: Google Chrome, Mozilla Firefox, Apple Safari and Microsoft Edge. This facilitates ease of access for users, without them having to download any additional software to their devices.

3.3 Experiments Controller

The experiments controller is activated and operates when there is at least one user executing an experiment. Its objective is to determine what is the next task in the current experiment, that the user should observe, and to keep track of time, results and responses in memory, so that all the data are collected properly and then they are transferred to the results processor.

3.4 Results Processor

The results processor is activated as soon as an experiment is completed and the corresponding command is given by the main processing unit. It will receive all the data and results, for the specific user and for the specific execution of the experiment, from the experiments controller and it will process them appropriately to prepare them for storage in the database. Once this process is complete the results will be sent to the database interface.

3.5 Database Interface

The database interface has only one task, to interact with the system database. This means both storing data and information and extracting them when they are needed by another component of the system. During these processes, data integrity checks are performed, as well as encryption and decryption when necessary.

3.6 Database

A database is used to store all the data and information of the platform. The database engine used is MySQL. Access to the database is password protected and the database contents are encrypted and secure. The database engine can easily be replaced if needed, since it communicates only with the Database Interface component, so changes would be required only to that component.

3.7 Machine Learning Module

The machine learning module is responsible for managing the neural networks, the models and all the necessary processes required for the training and predictions using machine learning. This specific implementation is based on Python programming language, Keras high-level neural network API and TensorFlow low-level machine learning platform (Joseph et al., 2021). This module is designed to be easily adaptable and extensible and to be able to provide customization for the neural network models for each experiment that exists in the virtual platform. Different sets of parameters and variables can be assigned each time to be executed in the machine learning algorithms. Data are retrieved from the database and after processing has been finished, they are stored back again with the additional information of prediction and the relevant confidence level. An important feature of the machine learning module is that it has the option to be configured to execute model training daily. Thus, a feedback loop is created and the system is trained each day with new data that are acquired in order to increase its predictive accuracy.

3.8 Robot Interface

The robot interface is an optional feature-addon for the overall operation of the virtual experimentation platform. It is necessary only when the option of the robotic experimenter is enabled to perform experiments and it acts as a communication channel between the virtual experimentation platform and the program that controls the actions of the robot. Communication with the robotic experimenter is handled through this interface component, so that in the future, multiple different robots could be made easily compatible with the virtual experimentation platform.

3.9 Robotic Experimenter

The robot used as a prototype for the platform is EZ-Robot JD Humanoid and it is a humanoid robot built to be accessible to users and suitable for educational and other purposes (Feil-Seifer & Mataric, 2005; Nourbakhsh & Dautenhahn, 2003). It has many features such as motion, sound output, object recognition and voice recognition. Its movements range from simple hand movements to complex movements that use all the robot's joints. All this is possible due to the robot's brain, which has the ability to communicate directly with all the robot's sensors and motors, as well as with external programs on computers and tablets that perform several processes which are necessary for the robot (Fong et al., 2003). Using external programs and resources for some processes saves battery life, thus improving autonomy while providing at the same time the potential to utilize more computational power which is available in the cloud.

The robot's dimensions are 15 cm long, 13 cm wide, 33 cm high and it weighs 1.33 kg. More specifically, it consists of:

- EZ-B v4 / 2 Wi-Fi Robot hardware controller
- EZ-Builder robot control software
- An anthropomorphic robot head with built-in camera and 9 RGB LEDs for each eye
- An anthropomorphic body with battery holder, supporting 6 high performance engines for the body
- 2 high performance hand motors
- 2 high performance motors for legs and ankles
- A 7.4v 1300mAh lithium battery

The robot can transmit live video and audio to its control device with the camera that is located in its head, thus enabling remote execution and supervision of robotic experiments without the subject being affected by human presence. It can also use the LEDs it has in its eyes to display different colors in different combinations. Robot speakers can produce audio, either pre-recorded (e.g. music, recorded messages), or created in real time by a microphone or text-to-audio converter.

The control software can easily and quickly record new movement actions and patterns for the robot, in turn making them available in the list of movements for immediate usage (Belpaeme et al., 2012).

Connection between the robot and the virtual experimentation platform is achieved with a custom software program that was specially developed and tailored to the needs of all experiments. This program is based on the Python programming language and the Web Sockets communication technology. It follows client-server architecture and it creates network connections to the virtual experimentation platform for synchronous data transfer between users. Also, at startup, it creates a network connection to the robot management program to transmit the appropriate commands to the robot. The complete architecture for the robotic experimenter is depicted in Figure 3.

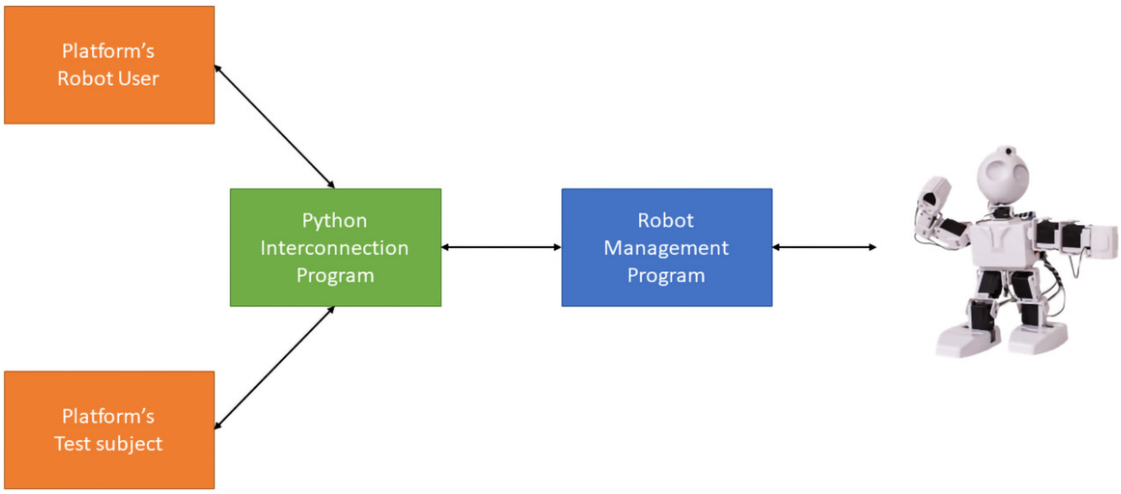

Figure 3. Robotic Experimenter Architecture

The robotic experimentation addon of the virtual experimentation platform is designed to support multiple robotic experimenters and multiple users-subjects executing experiments concurrently on different remote locations, keeping everyone's data and information secure and isolated.

4. Virtual Experimentation Platform Usage Demonstration

The virtual experimentation platform has many functionalities and it focuses in providing, not only a testing environment for users, but also open and anonymized data for interested third party researchers to be used for further analysis and potential studies. Throughout this chapter, the functionalities of each user role that is available in the virtual experimentation platform will be presented. There is a single point of entry, in the form of a login page (requiring username and password) in the virtual experimentation platform, which handles all different user roles. Automatically, depending on the username and password, each user is redirected to the appropriate home page depending on his/her role.

4.1 Administrator Role

The administrator role has full control over the virtual experimentation platform and usually only few accounts are granted with this role. It can access overall statistics about the platform like how many users are registered, how many experiments are available and how many times experiments or experiment-arrays have been executed. An example is depicted in Figure 4.

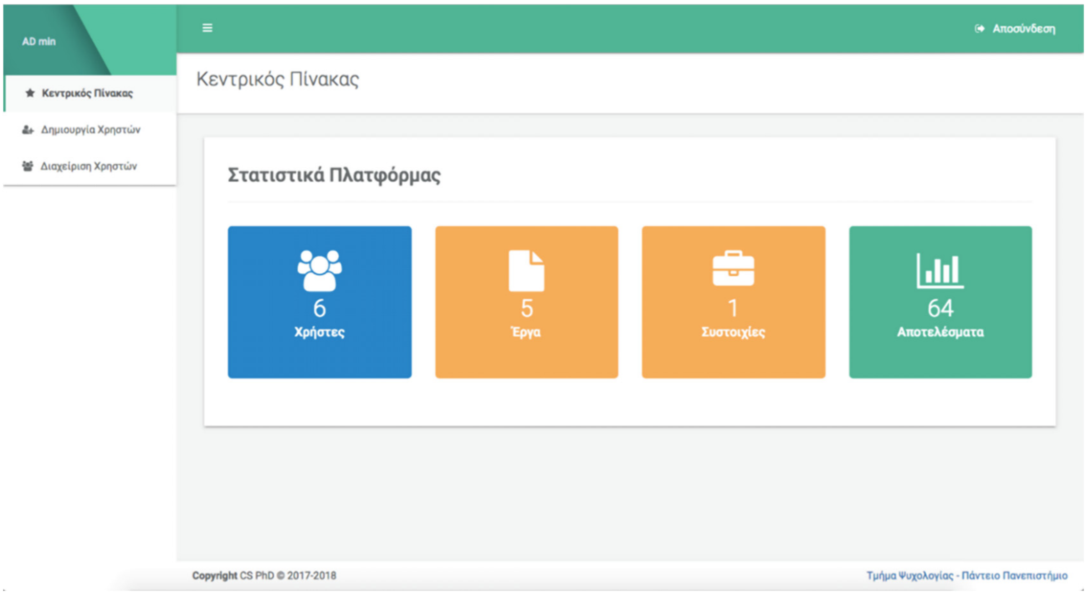

Figure 4. Administrator role statistics of the virtual platform

Another functionality that the administrator role has is that of user management. Administrators can create new users on the platform and assign specific roles to them. Also, administrators can enable and disable existing user accounts and view various information about them. A sample list of user accounts is presented in Figure 5.

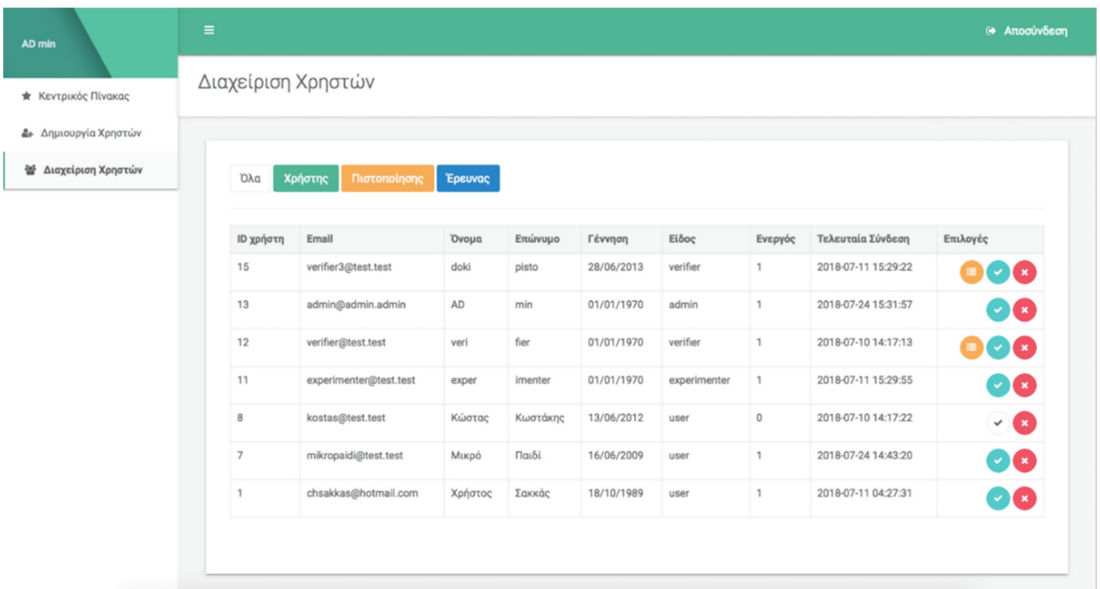

Figure 5. Administrator role list of user accounts

4.2 Data provider role

The data provider role provides access to anonymized data of experiments to external researchers, aiming to provide an open platform to share experimentation data. Those data are categorized by different experiments (Figure 6) and contain only information about the age of subjects at the time of experiment execution. No other personal information is provided, thus effectively anonymizing the subjects.

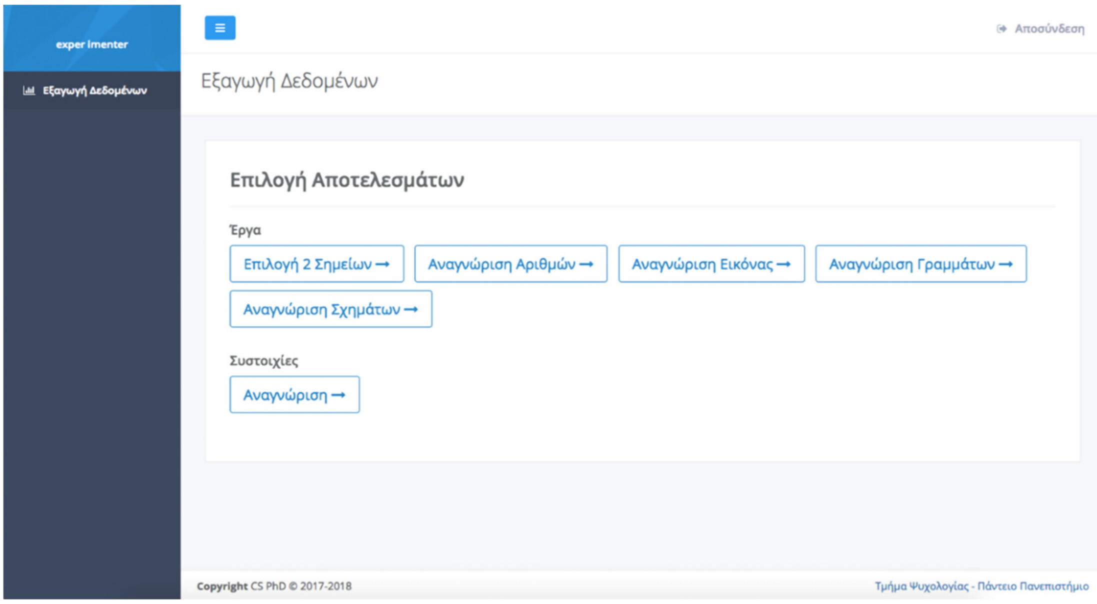

Figure 6. Data provider role experiment selection screen

A sample dataset of an experiment is depicted in Figure 7. Detailed data for each execution of the experiment are provided, like the encrypted user id, user age, datetime of execution, time of completion, tasks totals, execution times, results and averages. All those data are available for export and download in a csv file for further statistical analysis in specialized statistical programs, such as SPSS.

Επιλογή 2 Σημείων Εξαγωγή →

ID χρήστη	Ηλικία	Εκτέλεση	Χρόνος	Σύνολο	Μ.Ο.	Ελάχιστο	Μέγιστο	Δ1	Δ2	Δ3	Δ4	Δ5	Δ6	Δ7	Δ8	Δ9	Δ10	Πιστοποίηση
902ba3cda1883801594b6e1b452790cc53948fda	13	2019-03-10 15:58:51	38	10	1857	605	4482	1587	605	4482	1278	1568	796	1234	838	2405	3775	0
902ba3cda1883801594b6e1b452790cc53948fda	13	2018-07-11 15:27:48	30	10	615	509	981	582	570	636	511	520	580	509	722	981	534	1
902ba3cda1883801594b6e1b452790cc53948fda	13	2018-07-11 03:22:56	32	10	695	519	1088	553	519	599	1088	588	565	939	949	618	531	0
902ba3cda1883801594b6e1b452790cc53948fda	13	2018-07-10 18:14:45	30	10	710	517	1557	649	597	568	760	668	1557	587	517	546	651	1
356a192b7913b04c54574d18c28d46e6395428ab	32	2018-07-10 17:48:31	26	10	648	537	916	576	602	537	612	651	560	916	906	572	549	0
902ba3cda1883801594b6e1b452790cc53948fda	13	2018-07-10 16:39:42	27	10	656	522	948	640	522	573	699	586	569	542	569	948	913	0
902ba3cda1883801594b6e1b452790cc53948fda	13	2018-06-13 17:34:49	50	10	2781	765	11702	1260	975	2277	765	992	915	867	4636	11702	3421	0
902ba3cda1883801594b6e1b452790cc53948fda	13	2018-06-13 17:33:52	31	10	831	571	1132	767	767	788	956	617	571	1132	980	1108	628	0

Figure 7. Data provider role sample experiment data

4.3 Data verifier role

The data verifier role enables an optional but important functionality of the virtual experimentation platform. As this is an online accessible platform, some experiments can be designed to be publicly available without direct supervision from qualified experimenters. The results of these experiments cannot guarantee data integrity, thus there was a need to verify the data that were actually produced by experiments executed in a supervised environment. This is the functionality of the data verifier role. The verifier can choose which executions of the experiments are legit from a list of recent executions, depicted in Figure 8. Each verifier is assigned to multiple test subject accounts and they can verify only the experiment executions of those test subjects, in order to achieve isolation between users of the virtual platform and to avoid unauthorized changes.

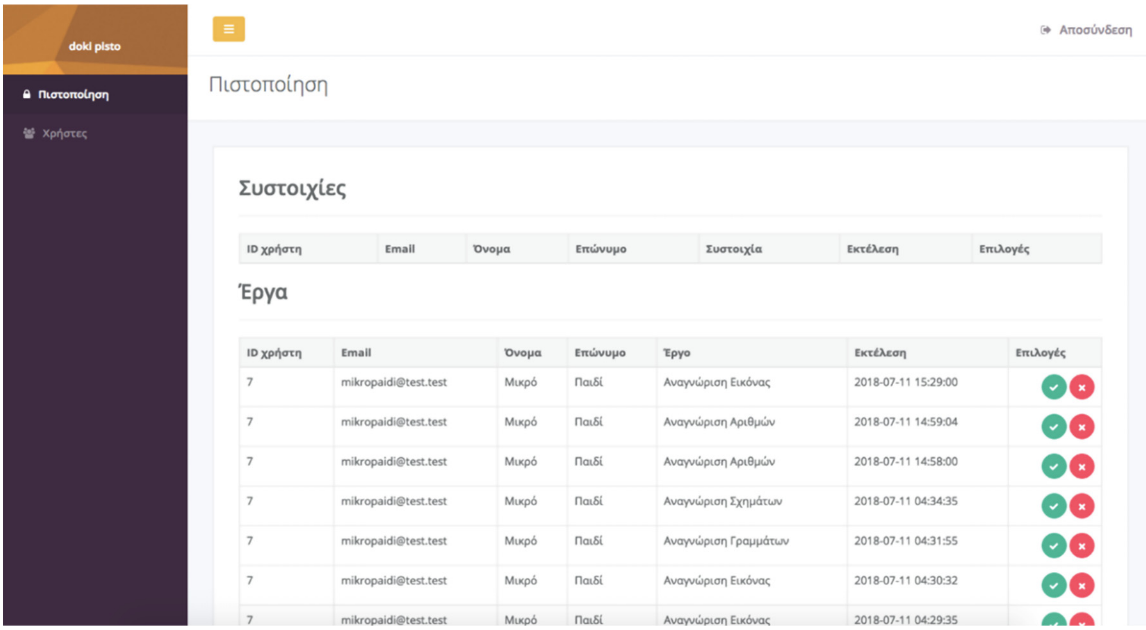

Figure 8. Data verifier role list of recent experiment executions

4.4 Robot user role

The robot user role enables the additional and optional functionality of having a remote-controlled robotic experimenter. It allows a humanoid robot, compatible with the virtual experimentation platform, to be controlled by simple buttons through a web browser. Simultaneously with sending commands for controlling the robot, additional commands are being sent to the test subject device that is executing the experiment, so that appropriate tasks and stages of the experiment are displayed on screen and they are synchronized with the movements and actions of the robot.

The home page of this user role is depicted in Figure 9 and it contains a button ("Connect with Experiment") which, when pressed, redirects the robot user to the control screen of the active experiment.

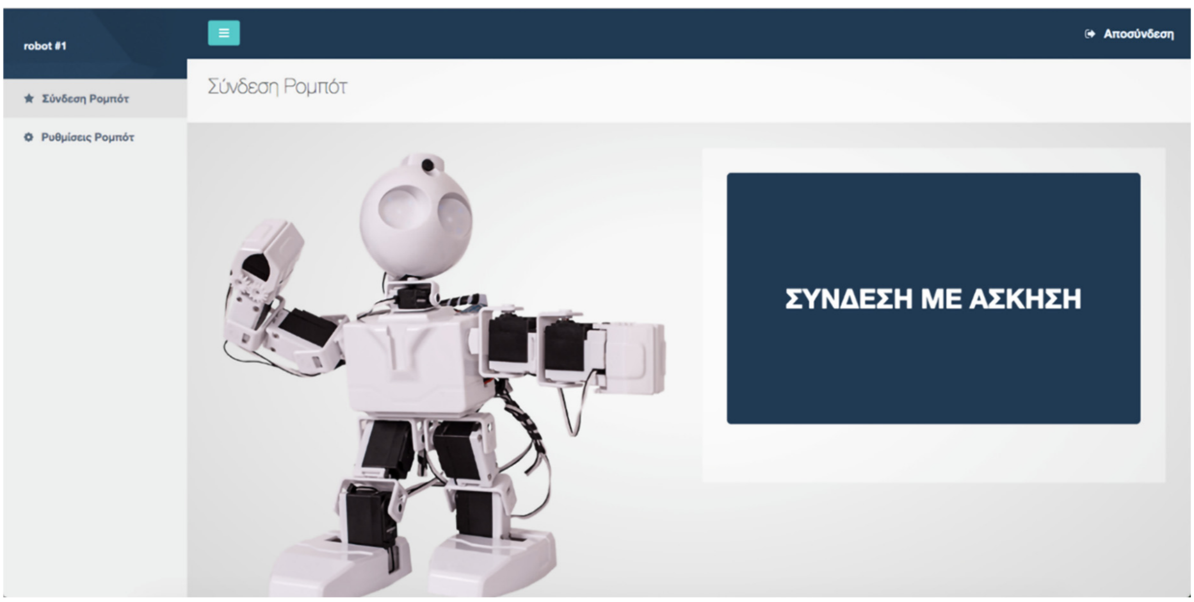

Figure 9. Robot user role home page

Just before the experiment control screen appears on screen, the program automatically detects if there is an active experiment ready for execution on a test subject user account, that requires robot experimenter. Association between robots and test subjects is configured by the settings screen, depicted in Figure 10. Then, the necessary commands and texts that are configured for the specific experiment are automatically loaded and displayed. Using the configuration screen, the robot user can configure the robot's name and IP address, so that every robot available in the virtual experimentation platform is uniquely identified and there is no conflict in the commands transmitted between the platform and the robots. This process is usually only needed once at the beginning, when installing a new robot on the virtual experimentation platform.

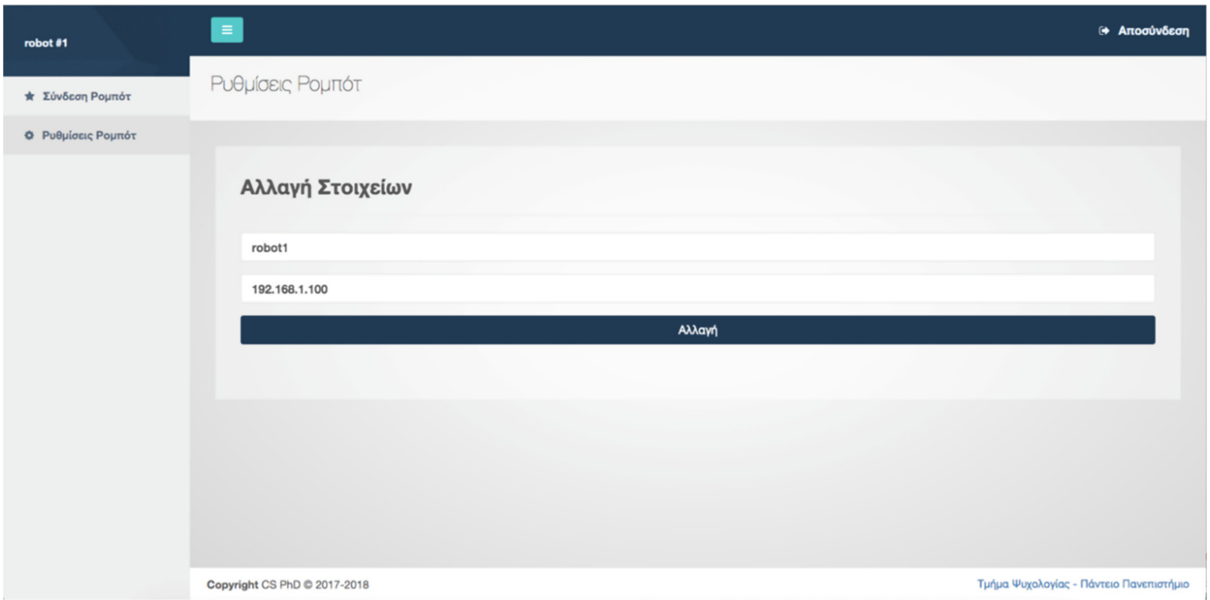

Figure 10. Robot user role configuration screen

The experiment control screen of the robot user role, depicted in Figure 11, contains all the necessary buttons required for each experiment. Each button corresponds to a command for a robot action coupled with commands for the content (visual and audio) that will be displayed on the device of the test subject which is executing the experiment.

The core commands of the active experiment are displayed on the left side of the screen. The commands are unique to each specific experiment, and they appear with the predetermined execution order, one by one. Also, there is information on the current, as well as the next step and text that the robot will produce from its speakers, in order to provide help and insight to the operator of the robot throughout the progression of the experiment.

On the right side of the screen there are generic actions that the robot can execute, which include different movement patterns or generic voice commands that can create general behaviors used to encourage, direct or motivate the test subjects. Although voice commands and movement commands can be executed concurrently, if the same type of command (e.g. 2 movement commands) is given at the same time, then the system will execute them sequentially.

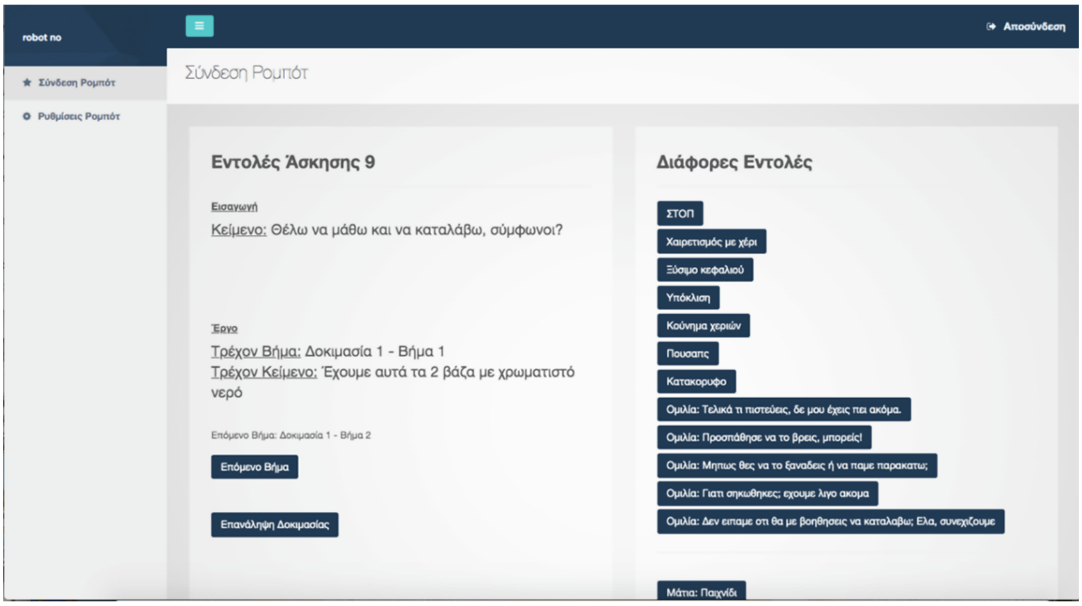

Figure 11. Robot user role experiment control screen

4.5 Test subject role

The robot user role enables the additional and optional functionality of having a remote-controlled robotic experimenter. It allows a humanoid robot, compatible with the virtual experimentation platform, to be controlled by simple buttons through a web browser. Simultaneously with sending commands for controlling the robot, additional commands are being sent.

The test subject role has access to a list of available experiments (Figure 12), filtered by age, and they can execute them on demand. Each experiment information card consists of a title, a brief description and metadata describing the measurements that are acquired by executing the experiment.

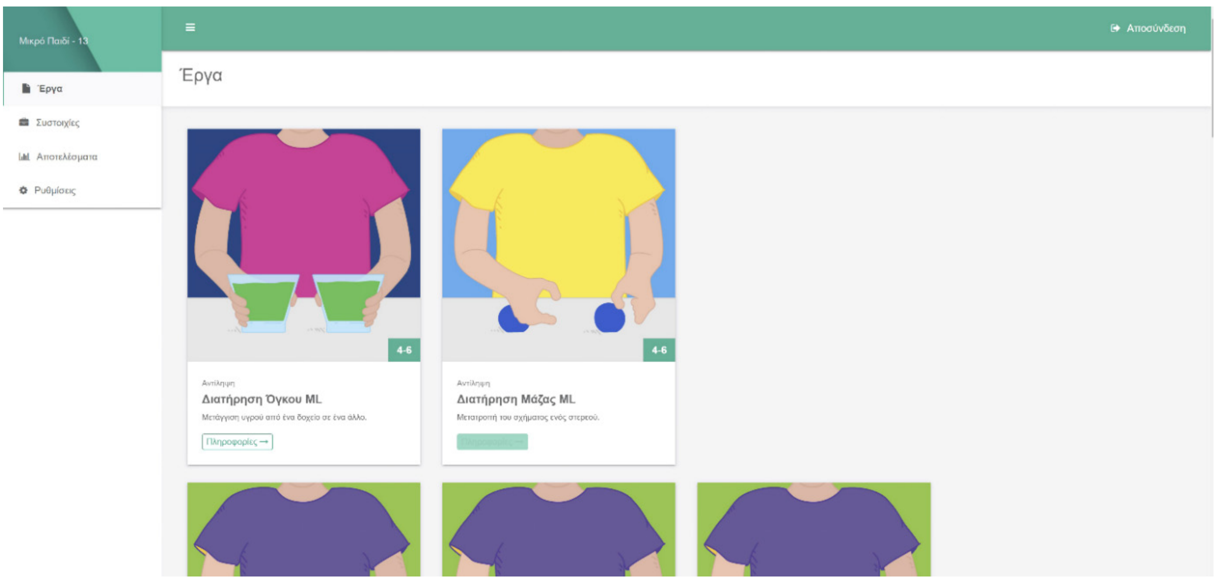

Figure 12. Test subject role list of available experiments

Additionally, the virtual experimentation platform has the option of enabling or not the access and visibility of experiment results to the test subject users that executed them. If this option is enabled, those results are presented per execution of each experiment, and they are numerical and graphical. An example of such results is presented in Figure 13.

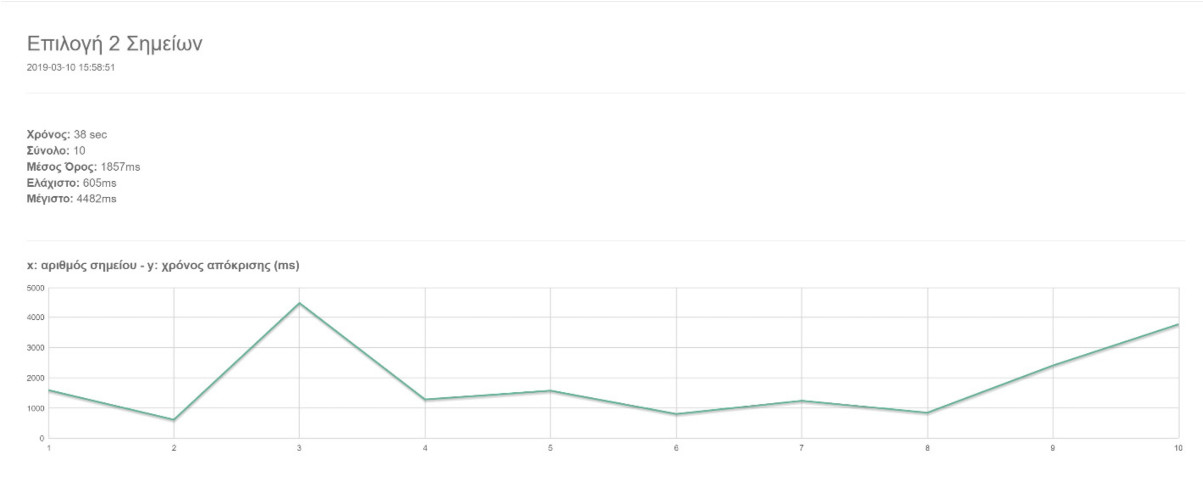

Figure 13. Test subject role sample experiment results

Each experiment implemented as part of the virtual experimentation platform has different characteristics, description, execution and measurements, thus making it impossible to present them all in the scope of this paper. In the next chapter a sample experiment (with three different modes of execution) is presented, in order to provide a better understanding of the whole virtual experimentation platform and its functionalities.

5. Method

To showcase, validate and provide an initial proof of concept for the virtual experimentation platform an experiment was selected. This experiment is based on Piaget's conservation tasks, and more specifically, it is the volume conservation of liquids.

Liquid conservation experiment requires the test subject to answer if the volume of the liquid present in different containers remains the same or if it changes when the liquid is transferred from one container to another. The first container is short and wide while the second container is tall and narrow. The introductory screen of this experiment, containing various valuable information, is provided by the system to the test subject and it is depicted in Figure 14.

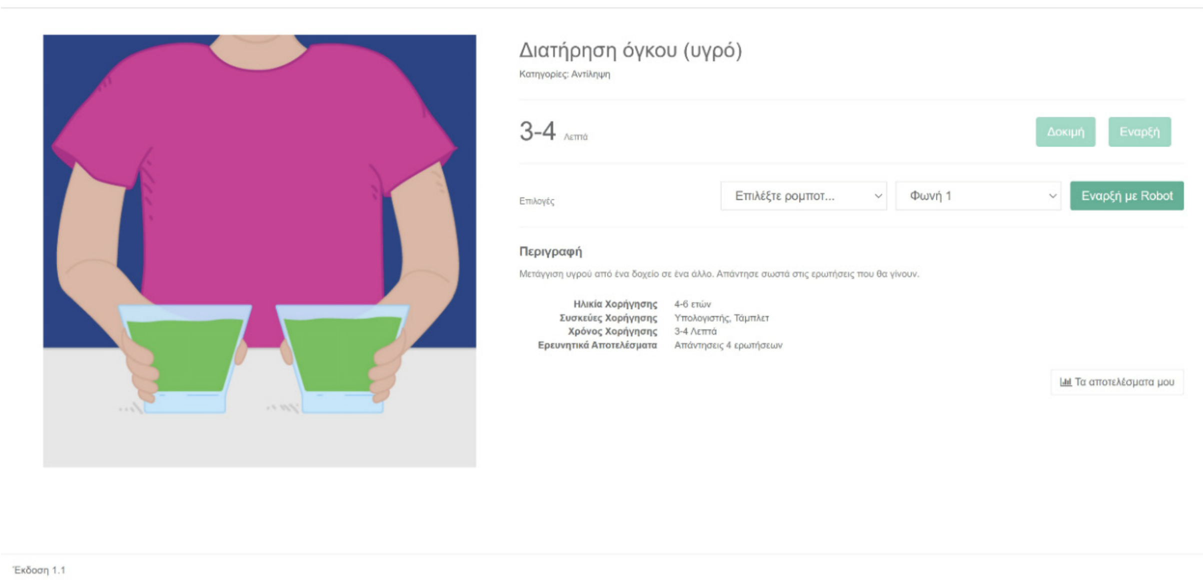

Figure 14. Volume conservation introductory page

The experiment is targeting children 5-6 years old, and it takes 3-5 minutes to complete. It can be completed either completely online and unsupervised, or with the help of an experimenter (human or robot). The research results that are produced by the system after the execution of the experiments are: i) total time needed for the completion of the whole experiment, ii) answer to each task provided by the test subject and iii) time needed for the test subject to provide the answer.

In order to assess all the available functionalities of the platform the experiment was executed in three different modes. The first 10 test subjects performed the experiment online in tablet devices. The second group of 10 test subjects again performed the experiment with the additional help of a robotic experimenter. The last group of subjects consisted of 120 participants, and it was used to gather data and perform the initial training of the machine learning module. Half of the test subjects in the first and second group were approximately 5 years old and the other half was approximately 6 years old. In the third group, 52 of the subjects were approximately 5 years old and the other 68 were approximately 6 years old.

The order of the tasks in the experiment is presented sequentially to the test subjects. These tasks fall into four different categories: the general concept of conservation, identity, compensation, and reversibility. A total of 4 tasks, one from each category, are used to complete the experiment. Random colors, containers and sizes are picked each time automatically and they are presented on screen.

Each individual task consists of 3 steps. Each step is described by voice, text and an image or a short video. The test subject at the end of the task, in step 3, is asked to select an answer by pressing the appropriate button (Figure 15). The available buttons for these two experiments are “SAME”, “MORE”, “LESS”, “DON’T KNOW” and they are displayed in random order for each task.

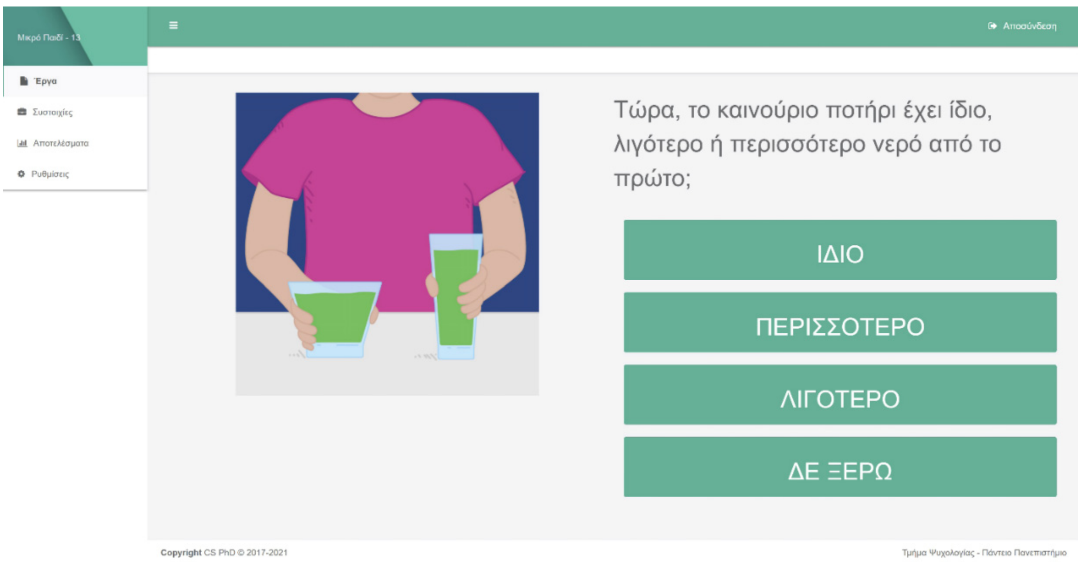

Figure 15. Test subject role experiment answer buttons screen.

In the end of the experiment execution, after all tasks are completed, there is the option to present the participant with the results of this execution. Such an example is depicted in Figure 16. Green color indicates correct answer and red color indicates wrong answer for the respective task.

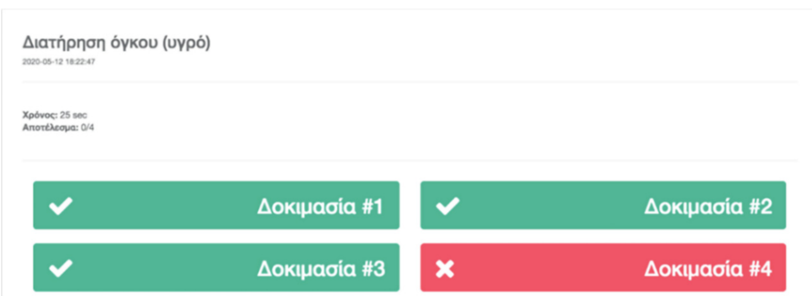

Figure 16. Test subject role experiment results

The neural network model used for this experiment consisted of four layers, one input, one output and two hidden layers (Figure 16). For the 3 first layers the rectified linear activation function (ReLU) was used. It is a linear function that will output the input directly if it is positive, otherwise, it will output zero. This has become the default activation function for many types of neural networks because a model that uses it is easier to train and often achieves better performance (Moolayil, 2018). The optimizer used was Adam, which features adaptive learning rates, bias correction and it has low memory requirements (Kingma & Ba, 2014). As this is a binary classification problem, since it has correct and wrong as possible answers the binary cross-entropy loss function was used. In combination with the sigmoid activation function from the output layer they create a synergistic effect for the following reasons:

- Probabilistic Output: The sigmoid function ensures the output is a probability, restricting the value between 0 and 1. This perfectly aligns with the binary cross-entropy function, which operates on predicted probabilities.
- Effective Learning Gradient: For efficient learning, the loss function should provide a good gradient. Owing to the mathematical properties of the sigmoid and binary cross-entropy functions, their gradient product is conducive to learning.
- Penalty for Incorrect Predictions: The combined use of these functions effectively penalizes wrong yet confident predictions. If the network makes a wrong prediction with high confidence, the sigmoid function will yield a value close to 0 or 1, leading to a large binary cross-entropy loss due to its logarithmic component.

The neural network created was trained for 400 epochs, in order to be accurate enough but also to avoid overfitting problems (Ying, 2019). Finally, after the machine learning module completed the training, the answers from the first two groups were fed into the system in order to evaluate the accuracy of the algorithm.

```
Using TensorFlow backend.
   conservation  identity  compensation  reversibility  age
0             0         0             0              0    5
1             1         0             1              1    5
2             0         0             0              1    5
3             0         0             0              0    5
4             0         0             0              0    5
['identity', 'compensation', 'reversibility', 'age']
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 4)                 20
_________________________________________________________________
dense_2 (Dense)              (None, 16)                80
_________________________________________________________________
dense_3 (Dense)              (None, 16)                272
_________________________________________________________________
dense_4 (Dense)              (None, 1)                 17
=================================================================
Total params: 389
Trainable params: 389
Non-trainable params: 0
_________________________________________________________________
Epoch 1/400
120/120 [==============================] - 1s 4ms/step - loss: 4.1260 - acc: 0.5917
```

Figure 16. Machine learning module model and training data screenshot

6. Results

The virtual experimentation platform functioned as intended in all experiment executions as presented in Table 1. Data from all the test subjects were stored in the database and they were available for further usage. Each test subject executed the experiment successfully in all modes. Thus, the virtual experimentation platform gathered a total of 600 answers, along with the accompanying research results for each one. The platform reached the desired 100% success rate in operational evaluation as it did not produce a single error during the execution of the tasks.

Table 1. Virtual experimentation platform liquid conservation execution results

Mode	Tasks	Conservation	Identity	Compensation	Reversibility	Total
Online	Success	10 (100.0%)	10 (100.0%)	10 (100.0%)	10 (100.0%)	40 (100.0%)
	Error	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
	Total	10	10	10	10	40
Robot	Success	10 (100.0%)	10 (100.0%)	10 (100.0%)	10 (100.0%)	40 (100.0%)
	Error	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
	Total	10	10	10	10	40
ML	Success	120 (100.0%)	120 (100.0%)	120 (100.0%)	120 (100.0%)	480 (100.0%)
	Error	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
	Total	120	120	120	120	480

For the analysis of the results both incorrect answers (“MORE” and “LESS”) and the answer “DON’T KNOW” were considered as wrong. In Table 2 the frequencies of the answers of the participating children are presented.

Table 2. Virtual experimentation platform liquid conservation answers.

Mode	Tasks	Conservation	Identity	Compensation	Reversibility	Total
Online	Correct	4 (40.0%)	6 (60.0%)	6 (60.0%)	6 (60.0%)	22 (55.0%)
	Wrong	6 (60.0%)	4 (40.0%)	4 (40.0%)	4 (40.0%)	18 (45.0%)
	Total	10	10	10	10	40
Robot	Correct	4 (40.0%)	5 (50.0%)	3 (30.0%)	6 (60.0%)	18 (45.0%)
	Wrong	6 (60.0%)	5 (50.0%)	7 (70.0%)	4 (40.0%)	22 (55.0%)
	Total	10	10	10	10	40
ML	Correct	45 (37.5%)	49 (40.8%)	50 (41.7%)	66 (55.0%)	212 (44.2%)
	Wrong	75 (62.5%)	71 (59.2%)	70 (58.3%)	54 (45.0%)	268 (55.8%)
	Total	120	120	120	120	480

In Table 3, all possible outcomes of the experiment executed for each age are depicted. It is observed that some outcomes have probability close to 0.5, which means that the prediction for Correct or Wrong is done with very small confidence level and it is close to luck. However, other outcomes have probability very close to 1 or 0 which means that they are very accurate and they have important predictive value. By using more data to train the model, accuracy is expected to increase. Also, it is clear that on average, the predictions for 6-year-old children are a little more confident than for 5-year-old children.

Table 3. Machine learning neural network model outcomes matrix with probabilities.

Age	Identity	Compensation	Reversibility	Conservation Prediction	ML Probability
5	Correct	Correct	Correct	Correct	0.78
5	Wrong	Wrong	Wrong	Wrong	0.08
5	Correct	Wrong	Correct	Correct	0.81
5	Correct	Correct	Wrong	Correct	0.67
5	Wrong	Correct	Correct	Wrong	0.25
5	Correct	Wrong	Wrong	Correct	0.65

5	Wrong	Correct	Wrong	Wrong	0.49
5	Wrong	Wrong	Correct	Wrong	0.12
6	Correct	Correct	Correct	Correct	0.78
6	Wrong	Wrong	Wrong	Wrong	0.06
6	Correct	Wrong	Correct	Correct	0.84
6	Correct	Correct	Wrong	Correct	0.67
6	Wrong	Correct	Correct	Wrong	0.18
6	Correct	Wrong	Wrong	Correct	0.68
6	Wrong	Correct	Wrong	Wrong	0.41
6	Wrong	Wrong	Correct	Wrong	0.08

To test the actual accuracy of the trained model, new data that were not in the training dataset needed to be fed in the system. In this case the answers from the first 20 participants (online and robot) were not in the training dataset for the machine learning module, so they were used as the validation dataset. Detailed results for each test subject are depicted in Table 4. After the subject id column, the following 4 columns contain the actual answers from the test subject. The final column contains the prediction for conservation from the machine learning module. Rows highlighted with gray background are the ones that presented difference between the prediction and the actual answer.

Table 4. Machine learning neural network model validation.

Test Subject	Age	Identity	Compensation	Reversibility	Conservation	ML Prediction
1	5	Wrong	Correct	Wrong	Wrong	Wrong
2	5	Correct	Correct	Correct	Wrong	Correct
3	5	Correct	Correct	Correct	Correct	Correct
4	5	Wrong	Wrong	Correct	Wrong	Wrong
5	5	Wrong	Wrong	Wrong	Wrong	Wrong
6	6	Correct	Wrong	Wrong	Wrong	Correct
7	6	Correct	Correct	Wrong	Correct	Correct
8	6	Wrong	Wrong	Correct	Wrong	Wrong
9	6	Correct	Correct	Correct	Correct	Correct
10	6	Correct	Correct	Correct	Correct	Correct
11	5	Correct	Wrong	Wrong	Wrong	Correct
12	5	Wrong	Wrong	Correct	Correct	Wrong
13	5	Wrong	Wrong	Wrong	Wrong	Wrong
14	5	Wrong	Wrong	Wrong	Wrong	Wrong
15	5	Correct	Correct	Correct	Correct	Correct
16	6	Correct	Correct	Correct	Correct	Correct
17	6	Wrong	Wrong	Correct	Wrong	Wrong
18	6	Correct	Correct	Correct	Wrong	Correct
19	6	Correct	Wrong	Correct	Correct	Correct
20	6	Wrong	Wrong	Wrong	Wrong	Wrong

The results indicate that the machine learning model evaluated by these data had 75% success rate (15/20 successful predictions) in predicting the conservation answer for new test subjects, if it already has their age and the answers for identity, compensation and reversibility. After the evaluation these data were used to additionally train the model in order to improve its accuracy for future predictions.

7. Discussion

In the literature numerous virtual learning/experimentation platforms are presented (e.g Bri et al., 2009; Georgouli, 2011; Kliziene et al., 2021), but most of them are outdated and they do not integrate modern technologies, like automated humanoid robots. Given that virtual applications for developmental study with children have gotten little consideration and that the methods used to execute such cognitive developmental studies are still lacking the inclusion of technology, the virtual platform described in this paper constitutes a precious tool. It is friendly to any user and answers to the scientists' interest for alternative ways of executing cognitive development experiments using virtual research techniques (Gijbels et al., 2021). This platform permits also to overcome cognitive obstacles mentioned in literature concerning a direct social interaction, as children are not influenced by the physical presence of the experimenter, which could negatively affect their behavior (McGarrigle & Donaldson, 1974).

Modern web technologies and methodologies were used in the design and development of the virtual experimentation platform (Gabarró, 2006), as well as software tests were performed (Myers et al., 2011) in order to validate the proper and complete functionality. Additionally, data from the 140 test subjects validated the tool and verified the hypothesis concerning the high level of functionality of the platform. It seems that the use of an automated robot in the role of the experimenter (Dautenhahn, 1999) offer the children an easy way of interacting with the questions, and an innovative gamified environment (Wei et al., 2011), which transforms a currently traditional process to an interesting experience. The proposed condition ensures equal roles to both participants, child, and robot-experimenter, during their interaction. Furthermore, a very special advantage of this virtual platform is, that no manipulation of the user's feelings or decision making in on-line communication occurs, contrary to suggestions of some recent studies (Fedushko, Kolos & Malynovska, 2019). Finally, the machine learning module presented in this study constitutes an important feature and tool that researchers can use to extract meaningful conclusions and connections. The experiment selected for the machine learning module contained a small number of variables to be analyzed by the neural network as its purpose was to just showcase the virtual platform and its features. Thanks to the platform's extensibility, researchers can leverage the platform capabilities and build as complex neural network as they want in order to optimally analyze their test data with the power of artificial intelligence.

8. Conclusion

This paper has presented a protype implementation of a virtual platform with robotic integration and machine learning capabilities for the execution of cognitive development psychology experiments in children. The paper analyzes the advantages of using a virtual platform for this purpose, due to configurability easiness and adaptability of the user interface to different type of experiments and questions, and fully describes the architecture and the functionalities of the proposed platform. Furthermore, significant contribution to the scientific community was made by means of open access to experimental data that may be used for further research. The implementation and platform usage were validated by a cognitive developmental experiment based on Piaget's theory, the conservation of liquid, and it was tested on 140 test subjects. The authors plan as future work to perform some qualitative and quantitative experimentation on the use of the proposed platform against traditional procedures, also identifying the superiority of the virtual experimentation platform use in the experimental process by increasing the interest of the children that participate, minimizing their fear of the experimental process and gamifying the whole procedure. Implications in health, educational applications and in children's social and cognitive development, overall, are evident and easy to reach by the use of the virtual platform proposed.

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