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Greening smart learning environments with Artificial Intelligence of Things[☆]

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ABSTRACT

This article investigates the functionality and applications of an Artificial Intelligence of Things (AIoT) system specifically designed for learning purposes. It presents three compelling case studies that pilot the AIoT system in various educational contexts. The first case study focuses on primary education and the use of a smart dashboard to monitor the state of plants in environmental awareness activities. In the second case study, conducted in higher education, variables such as CO_2 levels, light intensity, and temperature are monitored to generate personalised recommendations for creating an optimal learning environment through tailored adjustments. The third case study explores the potential of plants to identify human presence and activity patterns in learning environments. By utilising the AIoT system's capabilities, plant data is analysed to infer human presence and interactions. This innovative approach offers insights into understanding student behaviour and optimising learning environments based on real-time feedback from the plant ecosystem. Analysing these studies, the article deliberates on implications and future research opportunities in the realm of AI and IoT. It underscores the potential of AIoT systems in enhancing learning experiences, engaging students, and refining educational settings. The findings not only pave the way for future investigations, including model enhancements and privacy considerations but also emphasise AIoT's potential in reshaping the educational landscape. This article serves as a valuable resource for researchers and practitioners keen on leveraging the synergy of AI and IoT in educational contexts.

1. Introduction

Artificial Intelligence (AI) and the Internet of Things (IoT) have emerged as two of the most disruptive technologies in recent times, transforming various industries and revolutionising the way we interact with the world. In the field of education, these

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technologies hold immense potential to reshape traditional learning and teaching methodologies, opening up new possibilities for personalised and efficient education [1]. The convergence of AI and IoT has given rise to the concept of Artificial Intelligence of Things (AIoT), which combines the power of intelligent decision-making with the vast network of interconnected devices and sensors [2].

The Internet of Things (IoT) has significantly transformed the way of learning and teaching, particularly in higher education. IoT technology enables the reimagination and redesign of education systems, making them more versatile, adaptable, flexible, and responsive to rapid changes [3]. One of the key areas where IoT has made an impact is in the field of technology-enhanced learning (TEL). IoT-enabled computer-assisted learning systems have enhanced online and smart learning environments by enabling remote monitoring and screening of students' behavioural aspects and education scores [4]. These systems utilise smart devices and IoT applications to provide personalised and interactive learning experiences (ibid.). IoT has also played a significant role in the development of maker education, particularly in STEM disciplines (Science, Technology, Engineering, and Mathematics), which emphasises hands-on learning, problem-solving, and creativity, and enabling students to develop sustainable engineering abilities [5].

Artificial Intelligence (AI), on the other hand, promises to revolutionise the way we learn and teach, by fundamentally transforming the application and fabric of education. While IoT restructures and reshapes the physical landscape and outreach of data-generating devices, AI applies new ways and methods to interpret them. With its ability to process vast amounts of data, analyse patterns, and make "intelligent" decisions, AI holds enormous potential for enhancing the learning experience and optimising teaching methodologies. As AI continues to advance, it presents numerous opportunities for changing the way knowledge is imparted, acquired, and applied [6,7]. One of the key ways in which AI can transform learning and teaching is through adaptive personalised learning experiences. Traditional education often follows a one-size-fits-all approach, whereas AI can facilitate the customisation of learning paths based on individual student needs, preferences, and abilities, as well as context. By leveraging AI algorithms and machine learning techniques, educational platforms can adapt the content, pace, and delivery of instruction to cater to each student's unique learning needs, enabling them to progress at their own pace and achieve better learning outcomes [8].

Moreover, AI-powered tools can assist in content creation, generating interactive learning materials, and providing real-time feedback [9]. Additionally, AI can assist in the development of intelligent tutoring systems that offer personalised guidance to students, providing adaptive and individualised support throughout their learning journey. AI can transform education through the creation of smart learning environments (SLE). By integrating AI with Internet of Things (IoT) technologies, classrooms can become "intelligent" spaces that respond to student needs and adapt to their learning styles. AIoT-enabled smart classrooms are able to collect data from various IoT devices, such as sensors, wearables, and interactive whiteboards, to provide real-time insights into student engagement, attention levels, and comprehension. This data can inform teachers' instructional decisions and targeted interventions, thus helping them to tailor their teaching strategies to maximise student learning. By integrating AI algorithms with IoT devices, educational institutions can collect and analyse real-time data, providing personalised recommendations and feedback to enhance the learning experience. It should, however, not go unmentioned that there are some questions arising regarding the ethics and privacy related to these applications [10].

This article focuses on presenting an AIoT system specifically designed for learning purposes, aiming to harness the potential of AI and IoT in the context of plant-supported environmental education and digital green competences [11]. The proposed AIoT system utilises a combination of sensors to collect data from the physical learning environment, enabling the analysis of various ambient and soil variables connected to potted plants in the classroom. In addition, the plants themselves are used as sensors to identify the presence of humans and their physical activity within learning spaces based on the plants' electrical activity [12]. The system incorporates actuators to facilitate real-time monitoring and to provide customised recommendations for action based on the collected data. Furthermore, a visual interface featuring an avatar, serves as a user-friendly platform that learns from the data collected to deliver AI-generated recommendations for action towards well-being of students, teachers and plants coexisting in the classroom. The system opens up a wide range of learning activities by empowering learners and educators to explore a great variety of educational objectives such as understanding the effects of indoor plants on human well-being, training in digital data competences, exploring key Internet of Things components (e.g., sensors, actuators, microcontrollers), delving into renewable energies and strategies for resource conservation, or facilitating the acquisition of knowledge in Artificial Intelligence concepts [11].

The article is organised as follows. Section 2 describes the AIoT system. Section 3 describes three different experimental case studies piloting the AIoT system in educational contexts. Next, Section 4 analyses the combined results of the case studies and discusses opportunities for further research based on the lessons learned.

2. An AIoT system for learning

The AIoT system presented in this chapter has been designed to explore variables affecting plants and the environment in which they are located. It intends to support teachers in the creation of learning activities using AI, IoT, and indoor plants to train students in so-called digital green competences [11]. The interaction between stakeholders and the AIoT system aims to inspire authentic learning experiences to promote awareness of the benefits of using plants in learning spaces.

The AIoT system is an advancement of the previous IoT system that has been reported in recent publications [11,13]. The previous IoT system included: (1) Spike, an IoT device responsible for collecting data (sensors), storing it (on an internal SD memory card and remotely in the cloud), and offering real-time feedback on the telemetries; (2) IoT cloud platform, an online service that allows hosting the data collected by the Spike device when working in online mode, and a data panel to remotely display the information collected by the sensors (i.e., last telemetry and history timeline); (3) mobile messaging application; which teachers and students

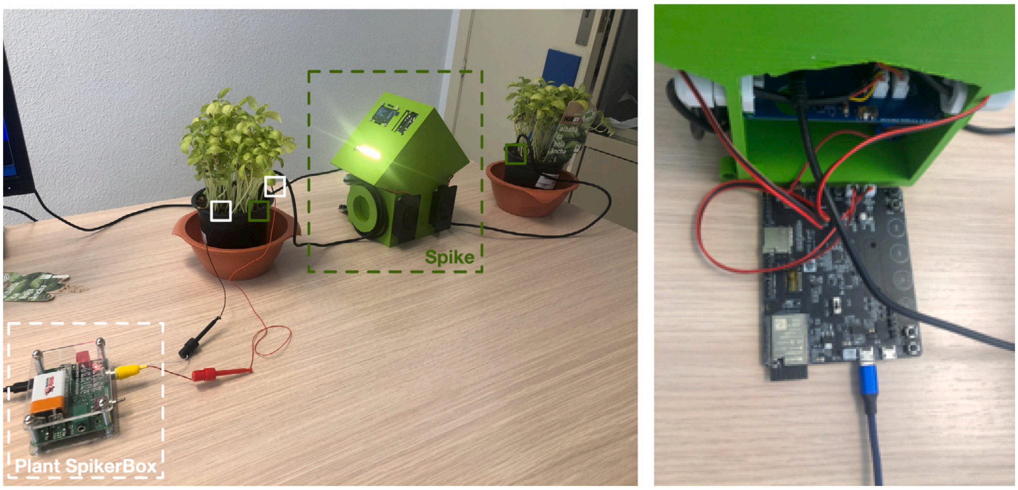


Fig. 1. AIoT system. (a) Front view: Spike and SpikerBox monitoring two basil plants; (b) Rear view: Voice assistant board.

can use to request the latest measurements made by any of the sensors installed in the system. In addition, teachers and students remotely receive alerts when specific scenarios occur (e.g., the recommended CO_2 thresholds are exceeded). These notifications can be configured to be sent to one person or to a group; (4) repository of learning activities in which teachers can create and share learning designs to guide their sessions and to inspire students and other colleagues.[1]

The AIoT system presented in this article includes additional functionalities that provide artificial intelligence to the system towards enhanced learning activities. Hence, we are addressing the core functions of smart learning environments (i.e., sense, analyse, and react [13]) to justify its intelligence. The AIoT system comprises of four devices that work in an independent yet interconnected way. These devices are illustrated in Fig. 1 and elaborated in the following subsections.

2.1. Spike: An IoT device to teach digital green competences

Spike is a 15 × 22 cm, and 3D-printed house with sensors and actuators that was designed to be placed in planters inside classrooms for learning purposes (see green-squared in Fig. 1). The Spike includes environmental sensors placed on the roof of the house (i.e., CO_2, humidity, temperature, and light). In addition, two soil temperature probes (rolled 1 metre long) have been installed on the side walls of the house to identify when watering is taking place, and to monitor the soil temperature of the plant. By placing a probe at each end of the planter, it is possible to know when the water is sufficiently distributed and, therefore, irrigation can be stopped. The probes can also be placed on different plants (as illustrated in Fig. 1(a)) with the aim of contrasting telemetry data from different species or locations/orientations within the classroom. Among other things, this can facilitate gamification activities where different individual students (or groups of students) take care of plants following different strategies. A restful Application Programming Interface (API) has been enabled so that third-party applications can access the data collected (and calculations: e.g., maximum, minimum, average) considering custom time ranges (e.g., last day, week, month, year). In addition to the OLED display (liquid crystal screen) representing the latest telemetry (see Fig. 1(a)), the system has been equipped with a bar of 8 coloured leds which are configured to represent the suitability of the levels in the form of a progress bar for colour-blind people (i.e., Excellent: 2 x blue led; Good: 4 x green led; Average: 6 x yellow led; Poor: 8 x red led). In addition, the system sends out alerts via mobile Telegram messages (text chatbot) that are triggered when pre-configured thresholds are exceeded.

2.2. Plant SpikerBox: A device to study plant neurobiology

In the realm of education, innovative technologies continuously emerge to enhance learning experiences and foster student engagement. By integrating the Plant SpikerBox (PSB) into educational settings, educators can unlock new dimensions of plant biology and provide students with hands-on opportunities to explore the electrical activities of plants. Plants, like humans and animals, possess electrical activity at the cellular level. Plant electrophysiology studies the electrical signals generated by plants, such as action potentials, which play a vital role in various plant physiological processes [14]. PSB serves as a tool that captures and amplifies these electrical signals, allowing students to witness and investigate plant communication and responses. PSB comprises a set of electrodes attached to the leaves or stems of plants (See white-squared in Fig. 1a). The signals are then amplified and processed, making them visible and audible through connected devices like smartphones or computers. This enables students to observe and analyse the electrical activities of plants, providing a unique perspective on plant physiology and behaviour.

[1] ILDE: https://ildeplus.upf.edu/teaspils/

Fig. 2. Smart visualisation dashboard in the classroom. (a) Individual use. (b) Collaborative use.

The incorporation of PSB in educational settings holds immense educational significance. Firstly, it offers students a hands-on experience, fostering curiosity and engagement. By actively participating in plant electrophysiology experiments, students can develop a deeper understanding of plant biology concepts, such as action potentials, ion channels, and signalling pathways. This experiential learning approach cultivates critical thinking, problem-solving skills, and scientific inquiry. Secondly, the PSB encourages interdisciplinary learning. As students explore plant electrophysiology, they engage with concepts from biology, physics, and chemistry. This interdisciplinary approach promotes holistic learning and encourages students to make connections between different scientific disciplines, broadening their horizons and fostering a more comprehensive understanding of the natural world. Lastly, PSB facilitates inquiry-based learning. Students can design and conduct their own experiments, formulate hypotheses, collect data, and draw conclusions. This hands-on, inquiry-driven approach empowers students to take ownership of their learning, enhancing their scientific literacy and nurturing a sense of scientific curiosity.

2.3. *Smart visualisation dashboard*

The AIoT system includes a visualisation dashboard that provides a user-friendly interface for monitoring plant conditions in educational settings. It features data visualisation interfaces, including line graphs and bar charts collected by the Spike during a period of time. These visualisations (mirroring mode of the dashboard) allow customisation, comparisons, text and image annotation, as well as snapshot visualisation (See Fig. 2).

The visualisation dashboard features a smart component that incorporates an alerting mode triggering pop-up notifications when critical events that might have an impact on humans or plants occurred (e.g., "The temperature has increased by 8% in one week"). "The last observation was introduced 5 days ago", or "Yesterday's highest temperature was at 12:30 p.m".. The purpose of such alerts is then informative based on the data collected. In addition, the smart component also incorporate an advising mode that provides suggestions and guidance on how to react to such events (e.g., "The temperature has increased by 8% over last week; check the plant's location as it might be too close to the heating system"). "The last time the plant was watered was 5 days ago; have you watered it enough?", or "Today's highest temperature is predicted to be at 12:30 p.m.; make sure the sunlight is not too direct". The purpose of these alerts is to provide information and offer suggestions about possible actions that improve the situation as assessed based on the data (See Fig. 3). When the dashboard is in the alerting or advising modes, users still have access to the mirroring mode visualising the data.

2.4. *Voice assistant*

Interactive assistants have emerged as a powerful tool to support learning experiences [15]. The integration of voice assistants brings forth a new dimensions of interactivity and accessibility [16]. The voice assistant implemented into the AIoT system includes an ESP32 LyraT microcontroller, Google speech-to-text capabilities, and two speakers. This integration allows students and teachers to interact with the system using natural language queries related to the monitored plant and its environment. The voice assistant utilises Google speech-to-text technology to convert spoken language into text, enabling seamless communication between the user and the AIoT system (See Fig. 1.b). Once the voice query is transcribed, the system employs a restful API based on an IoT cloud platform (i.e., Thingsboard[2]) to retrieve the required information from the collected telemetries. By formulating questions about

[2] Thingsboard IoT cloud platform: https://thingsboard.io/

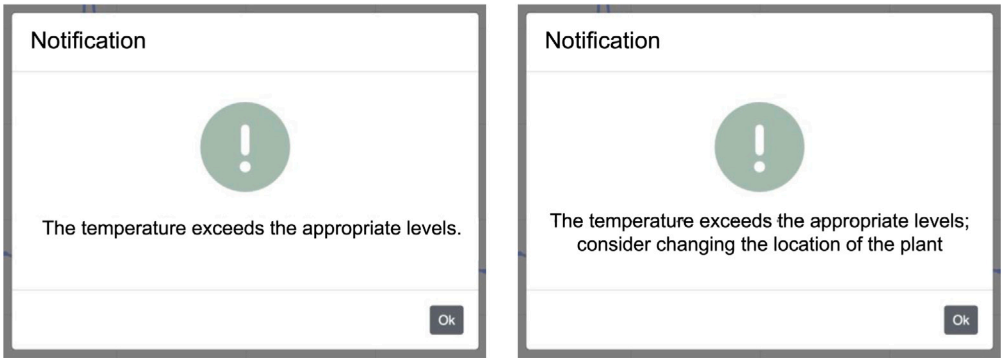


Fig. 3. Smart visualisation dashboard modes: (a) Alerting mode. (b) Advising mode.

the plant's well-being or specific data ranges, users can request valuable information such as the maximum, minimum, and average values of plant-related variables recorded by the sensors. The integration of a voice assistant in the AIoT system promises significant added educational value. First and foremost, it facilitates a user-friendly and intuitive interaction between students, teachers, and the AIoT environment. Students can engage in conversational exchanges with the system, making the learning process more interactive and engaging. The voice assistant acts as a virtual guide, answering questions and providing real-time information, enhancing students' understanding of the plant's condition and its environmental factors. Furthermore, the voice assistant promotes inclusivity and accessibility in the learning environment. Students with varying abilities or learning preferences can benefit from the speech-based interaction, enabling them to access information and participate actively in the learning process. The voice assistant eliminates barriers to communication and ensures that all students can engage with the AIoT system and benefit from its insights. Among other things, the voice assistant fosters the development of communication and critical thinking skills. Students are encouraged to articulate their questions clearly and formulate precise queries. They learn to frame their enquiries and interpret the responses received, nurturing effective communication skills and enhancing their ability to analyse and interpret data.

2.5. Plantagotchi: An avatar for serious games

The avatar, Plantagotchi, serves as a virtual representation of the human-plant's well-being, acting as a visual indicator of the impact of environmental conditions on their health. By associating the avatar's lifespan and point system with the adherence to recommended thresholds, students are motivated to make informed decisions and take appropriate actions to maintain the plant's vitality [17]. Plantagotchi's lifelike attributes and interactive nature enable students to form an emotional connection with the avatar and, therefore, with the connected plants. This emotional engagement enhances the learning experience by fostering a sense of responsibility and accountability for maintaining optimal classroom conditions. As the avatar's points decrease more rapidly when thresholds are exceeded, students are incentivised to actively monitor and control the environmental variables within the specified ranges.

Plantagotchi is based on the image of a lizard. Its lifespan lasts 18 days, equivalent to 100 points, which are constantly deducted from the first day the avatar is born until its final day when the avatar "passes away". The points are decremented more rapidly when the thresholds are exceeded, indicating a failure to meet the recommended ventilation [18], or temperature (maximum in winter; minimum in summer) [19]. The avatar provides actionable recommendations when the thresholds are surpassed, enabling the student to moderate these variables and achieve appropriate measurements. The objective of this serious game is to keep the avatar alive for the entire 18 days, and the player who successfully accomplishes this goal emerges as the winner. This implementation demonstrates a creative and engaging approach to fostering student participation and learning, as well as caring for a healthy environment.

3. Three case studies piloting AIoT in educational contexts

In this section, we present three case studies showcasing the application of the AIoT system in diverse educational levels. These case studies exemplify its versatility and effectiveness in enhancing learning experiences across different educational contexts. Through these case studies, we aim to shed light on the transformative impact of AIoT in education. By embracing innovative approaches and leveraging AIoT technologies, educators and learners alike can unlock new dimensions of knowledge acquisition and foster a deeper connection with the natural world.

3.1. Case study 1: Using a smart dashboard to promote environmental awareness in primary education

The first case study was conducted in primary education. The case study used the AIoT system with an emphasis on investigating the effects of the data visualisation dashboard in its different configurations (simple: mirroring mode, smart: alerting or advising

Table 1
Structure of the learning activities and experimental design for the workshop.

Session	Time	Description	Experimental design
1	15’	Pre-test	Collect pre-test data
	15’	Presentation on plants, spike, and dashboard	Same for all conditions
	20’	Exploration of the spike prototype and the dashboard	Application of experimental conditions
	30’	Brainstorming mural: Hypothesis mural regarding the effect of environment on the plant	Collect activity data
2	10’	Presentation: Data analysis concepts	Same for all conditions
	30’	Plant observation: discover which plant they are given based on the observable characteristics	Same for all conditions
	15’	Tutorial on the visualisation dashboard	Application of experimental conditions
	60’	Canvas with data analysis exercises	Application of experimental conditions
3	25’	Presentation: Climate change & effects on plants	Same for all conditions
	15’	Facts about plants: True or false game	Same for all conditions
	25’	Activity: identify healthy vs unhealthy plant based on data	Application of experimental conditions
	15’	Post-test	Collect post-test data
	30’	Mural: Reflection on the importance of plants and emotional aspects	Same for all conditions

modes). The proposed learning activities in this case study aimed to foster children’s understanding of the impact of environmental conditions on plants and the role of climate change, while introducing data analysis concepts. The dashboard was used by children for monitoring the health status of plants while completing a set tasks (See Fig. 2), to display the ambient and plant measurements (i.e., temperature, humidity, soil moisture, CO_2 and light). The research questions were: RQ1 — Do learning activities using the dashboard of the proposed AIoT system promote environmental awareness? RQ2 — Can we observe differences in the activity performance depending on the mode of use of the dashboard (simple mirroring vs. smart alerting or advising)?

3.1.1. Methods

The setting for the study was a three-session workshop integrated in school time. The learning activities were organised in three phases, corresponding to the three sessions of the workshop, in which students had to formulate questions and hypotheses, analyse the data collected, and draw some conclusions, respectively. The activities were not restricted only to data analysis concepts but also included other learning goals, exploring the possibilities of the visualisation dashboard in a classroom, such as activities related to plant care, anthropogenic action and climate change, and emotional aspects. The workshop emphasised inquiry-based learning, problem-solving skills, and collaboration among the participants.

A total of 45 participants from a primary school in the province of Barcelona (Spain) took part in the workshop. Participants were students from three classes with 15 students per class and age M(SD)=11.5(0.6). The sessions were organised as illustrated in Table 1. The three sessions of the workshop (approx. 2 h of duration each) were scheduled one or two weeks apart from each other. Most activities were performed in small groups of 4-5 people except for individual and plenary activities. The activities in the workshop were structured so that each session included a description of theoretical concepts, interactive presentations, and hands-on activities using the dashboard and paper worksheets.

Each class received one potted plant and two datasets: the first dataset, which was collected using the Spike, represented ideal measurements for the conservation of the plant and the environment for one week; the second dataset, which was elaborated by making specific adjustments to the first dataset, simulated the measurements that would correspond to inappropriate care of the plant and the environment. Through the activities, students had to explore and differentiate these two plant scenarios. Each class was assigned with a dashboard system condition (simple mirroring vs. smart alerting vs. smart advising) throughout all the sessions of the workshop, following a between-groups experimental design. For the proposes of the controlled case study, a total of 57 notifications per condition (alerting and advising) were created: 15 for the first session, 20 for the second session, and 22 for the third one. The alerts in the alerting and advising conditions matched, in the sense that the advising alerts provided a more complete version of the alerting ones, with the information about relevant events (present in the alerting system as well) coupled with the corresponding suggestions or interpretations (only in the 29 advising system).

Students were asked to complete a pre-test and a post-test as part of the data collection to analyse both the impact of the workshop on environmental awareness and of the different visualisation dashboard modes. Both tests incorporated two relevant sections to assess different aspects. The first section involved a series of statements related to environmental awareness, for which students were required to rate their agreement on a scale of 1 to 5. The second section consisted of a combination of open-ended and closed questions that aimed to evaluate their knowledge regarding the impact of environmental factors on plants and their problem-solving skills. Data from the activities, including individual and group worksheets, sticky notes, and other observations, was also collected.

3.1.2. Results

Regarding RQ1, the comparison of the pre-test against the post-test revealed a significant positive impact of the workshop activities on the goal to promote environmental awareness. The ratings of the statements related to environmental awareness were compared through paired t-tests, showing significant differences in the statements as illustrated in Fig. 4. To further qualitatively

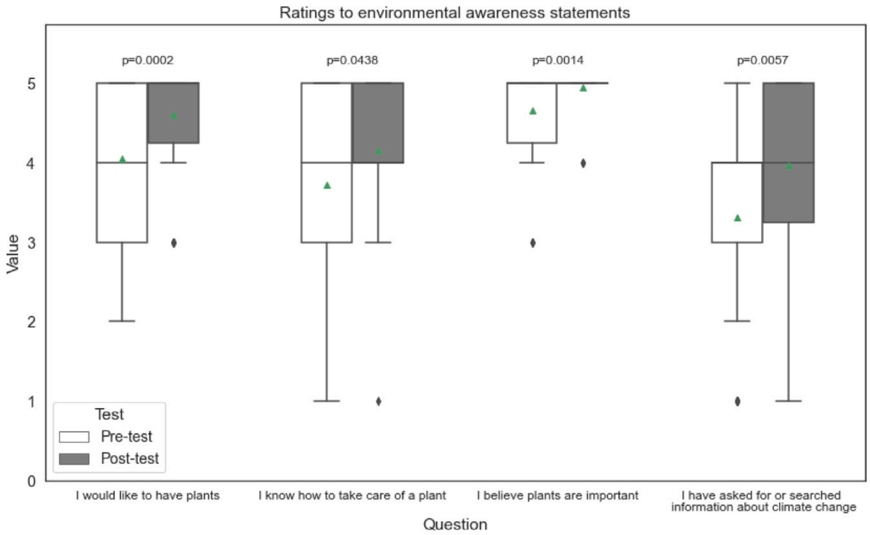


Fig. 4. RQ1. Comparison of ratings (from 1 to 5) to environmental awareness statements.

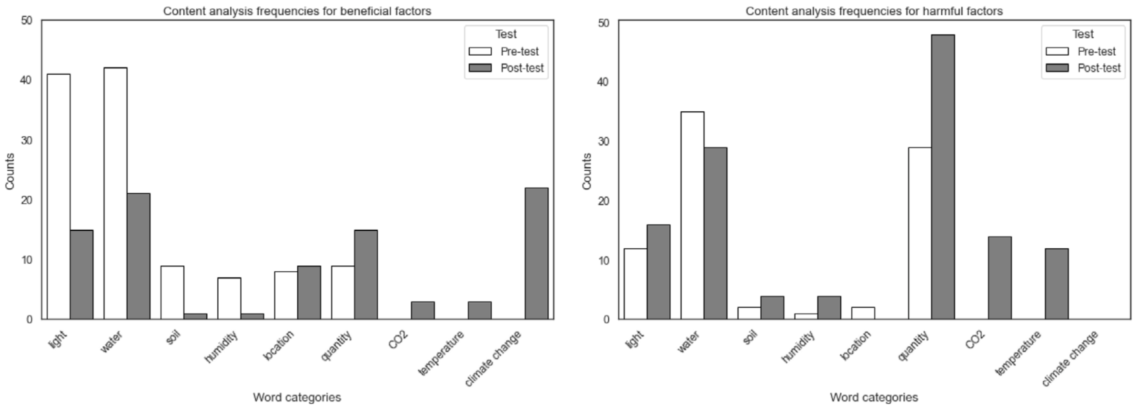


Fig. 5. RQ1. (a) Frequencies of the word categories related to the beneficial factors for plants. (b) Frequencies of the word categories related to the harmful factors for plants.

understand student's improvement of their environmental awareness (RQ1), we compared their answers in open-ended questions. For the open-ended questions regarding the beneficial and the harmful factors for a plant, we performed a content analysis by means of a Pearson's chi-square test. We considered the frequency of the relevant words for the whole group of participants, and only included those word categories with at least 5 counts in one of the groups to adjust to the requirements of the test. Significant differences were found both for the beneficial factors (p-value = 1.676392e−09) and the harmful factors (p-value = 0.000291). Fig. 5 shows how although light and water categories are the most recurrent environmental factors in both tests, other factors appear in the post-test, such as temperature, CO_2, and climate change related. Fig. 5 shows how none of the answers in the pre-test considered the temperature or CO_2 as harmful factors whereas they were counted multiple times in the post-test. Also, the difference in the quantity category shows that these factors were accompanied by some quantitative adjustment.

Regarding the potential differences between the simple and smart modes of the dashboard (RQ2), this study found no significant association between the dashboard system and the problem-solving performance by means of direct comparison of the pre-test and post-test. However, it found some significant differences between conditions (modes used) in other activities of the workshop and in related queries in the post-test. In the first session, significant differences were observed in the generation of hypotheses among the experimental groups, through a Kruskal–Wallis test (p-value=0.044611), with the mirroring and alerting groups producing more unique hypotheses compared to the advising group. In the second session, participants completed a canvas with various data analysis-related activities. Significant differences were found in two of these activities: the judgement of the plant's health state over the week based on the data and in identifying which days the plant was watered, through a Chi-square test (p-value=0.014239) and a Mann–Whitney U between control and advising conditions (p-value=0.044690), respectively. The analysis showed that groups receiving notifications – alerting and advising – performed better in these activities compared to those using mirroring mode. In the third session, participants worked on a problem-solving activity to identify a healthy and an unhealthy plant based on their datasets.

Significant differences were observed in the reasoning behind their decisions, coded into four categories, through a Chi-square test with the p-value=0.039517. The groups in the alerting and advising conditions mentioned factors related to climate change, such as increases in temperature and CO_2, as the basis for their identifications. On the other hand, the group in the mirroring condition did not specifically refer to these factors. Instead, they made less specific observations, such as the dataset having "worse factors" or being more "unbalanced". Overall, the workshop activities provided valuable insights into the impact of different dashboard systems on students' problem-solving skills and data analysis capabilities. Finally, in the individual post-test, students were asked again to provide reasoning for the unhealthy plant's state and to propose solutions to avoid such conditions. The analysis did not show significant differences between the experimental groups in the correctness of reasonings or the frequency of relevant words. However, in questions related to climate change indicators, we observed that the alerting group tended to perform better in these aspects compared to the advising and control groups.

3.1.3. Conclusions

This case study shows an innovative way to effectively promote environmental awareness among primary school students. On the one hand, the system used and the activities proposed illustrate the potential of the approach to transform the classroom into a smart space able to provide children with real-time information about plans in the classroom. On the other hand, the different modes of the dashboard have shown its capacity to support diverse types of learning benefits. For example, in the case of the simple mode (non-smart/mirroring visualisation) and the smart alerting mode, students were able to generate more hypotheses for the inquiry-based learning task if compared to the smart advising mode. One possible explanation is that in the advising mode, students receive a high level of scaffolding that hinders their creativity in this type of task. On the other hand, smart modes (learning and advising) led students to generate richer self-explanations in terms of causing factors related to climate change. These results also show the potential of the proposed AIoT system to provide personalised guidance to students based on their progress and performance (e.g., offer advice only when self-explanations are not sufficiently rich), or to adapt to the needs of the educational scenario (decrease advice and adjust alerts to boost creativity).

3.2. Case study 2: Profiling green classroom recommendations with predictive analytics based on sensor data

The second case study was conducted in a university setting in two phases: In the first phase, an avatar called "Plantagotchi" [17] (see Fig. 6) and a voice assistant [20] were developed to provide alerts and recommendations aimed at promoting environmental awareness by (a) moderating energy consumption in the classroom (i.e., lighting, air conditioning, and heating), (b) alerting about potentially hazardous scenarios for contagion (such as colds, COVID, or other viruses) by monitoring CO_2 levels in the classroom, and, (c) monitoring potentially unfavourable conditions for plants located within the classroom. In this way, the avatar offers real-time recommendations for actions to students or teachers when specific thresholds are exceeded for lux, temperature, humidity, or CO_2. In the second phase, which is reported in this article, the Spike was deployed to collect data over a period of 3 months in a classroom. Here, a predictive model based on sensor data is designed to configure the AIoT system (avatar and voice assistant features) with action recommendations that enable students and teachers to anticipate scenarios of energy wastage or potentially unhealthy conditions for both plants and individuals. This involves taking proactive actions to address such scenarios in advance (for instance, turning off lights, reducing heating or air conditioning, opening doors, or watering plants). This article elaborates on the second phase of the study, focusing on the utilisation of the Spike to collect data and the subsequent development of the predictive model. The aim was to empower the AIoT system with actionable insights, enabling stakeholders to pre-emptively address energy inefficiencies and potentially adverse conditions, thereby promoting a healthier and more sustainable classroom environment.

Some studies have already explored the use of avatars (e.g., virtual tree [21]) or virtual assistants to provide personalised feedback on environmental conditions and consequently suggest actions towards healthy and sustainable learning environments (i.e., noise pollution [22,23], asthma management in children [24], air pollution [25], climate change [26]). Others have explored the use of gamification to motivate behavioural changes and promote energy efficiency in educational settings [27,28]. Nonetheless, to the best of our knowledge, none of these studies configured an avatar to promote environmental awareness based on predictive models in learning contexts. Therefore, we applied the well-known auto-regressive integrated moving average (ARIMA) models to investigate recommendations that anticipate the three scenarios described below using 3 months of data collection in a classroom and the Plantagotchi avatar.

3.2.1. Methods

The data file we were working with was obtained from the measurements made by the Spike. This dataset consists of 2161 rows and 8 columns. The characteristics of the data are as follows: Observation date (*Timestamp*), carbon dioxide concentration CO_2, humidity (*humidity*), indoor lighting (*light*), soil temperature (the sensor gives two measurements: *soilTemp1* and *soilTemp2*), and ambient temperature (*temperature*). The date range corresponds to three months: April, May and June 2023 (91 days). The measurements were sampled every hour, and a clean-up of the dataset was carried out to extract the appropriate information for the forecast: missing data were checked, sensor reading errors were corrected, and a new variable (*soilTemp*) was created as an average of *soilTemp1* and *soilTemp2* because both probes were allocated in the same planter. In addition, an exploratory analysis of the refined dataset was carried out. With this analysis, the trend of the measured variables, the main descriptive statistics and the correlations between the quantitative variables were determined (see Fig. 7). The correlation analysis indicates that there is a positive linear correlation between the variables temperature and soilTemp, with a value of 0,77. These two variables are the only ones that could be estimated with a linear model. However, due to the nature of the data, the statistical model shows other

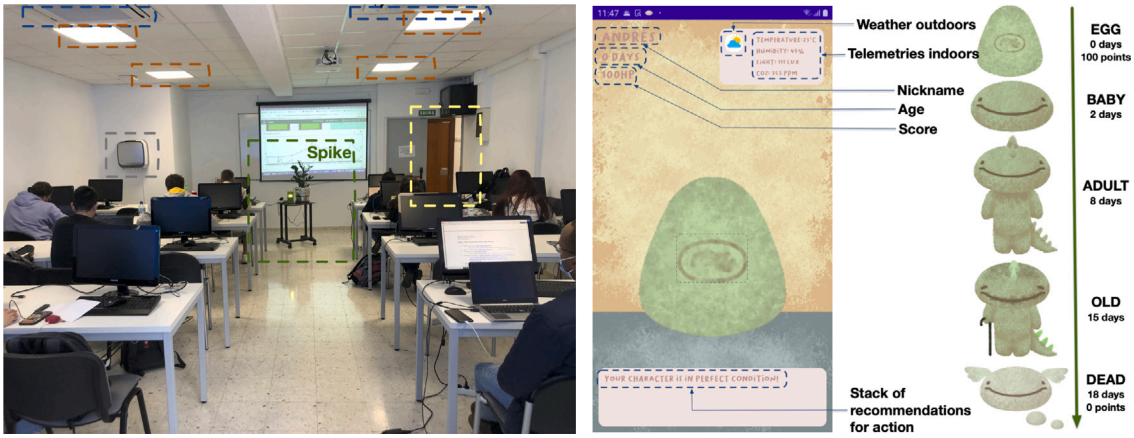
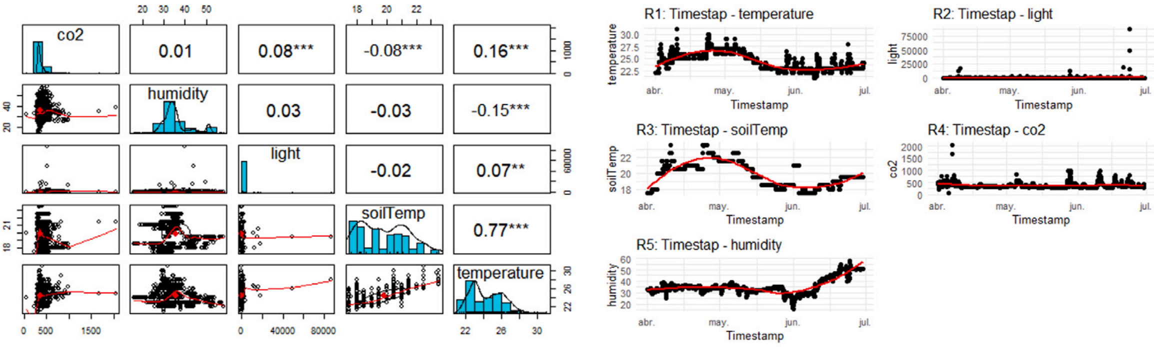


Fig. 6. Collecting data from the classroom towards (a) Classroom setup: air conditioner to moderate temperature (blue), light system (orange), air purifier to moderate CO_2 (grey); door open for cross ventilation (yellow); windows and shutters are in the back of the picture (not visible) (b) Plantagotchi's lifecycle. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)




```
      co2              humidity          light            soilTemp         temperature
 Min.   :  46.0    Min.   :16.00    Min.   :    0.00   Min.   :17.50    Min.   :21.00
 1st Qu.: 308.7    1st Qu.:32.00    1st Qu.:    0.00   1st Qu.:18.50    1st Qu.:23.00
 Median : 333.0    Median :34.00    Median :   11.67   Median :19.50    Median :24.00
 Mean   : 365.2    Mean   :35.66    Mean   :  217.13   Mean   :19.84    Mean   :24.38
 3rd Qu.: 384.0    3rd Qu.:37.00    3rd Qu.:   72.00   3rd Qu.:21.00    3rd Qu.:26.00
 Max.   :2039.3    Max.   :58.00    Max.   :86500.00   Max.   :23.50    Max.   :31.00
```

Fig. 7. Correlations and key descriptive statistics for quantitative variables.

relationships which, although not linear, should be taken into account: temperature and humidity (−0,15), temperature and CO_2 level (0,16), temperature and light (0,07), CO_2 level and light (0,08), and finally, CO_2 level and soilTemp (−0,08). In fact, this statistical analysis confirms that, for the scenario described, these variables can be related to create a predictive model.

The predictive model we are using works best when the data have a stable or consistent pattern over time. This means that the variance and mean of the data have to remain constant over time. When plotting the variables as a function of time, due to the chosen interval and the nature of the data, we note that it is not easy to ensure a certain stationary component. Therefore, to test the stationarity of the data, we use the Augmented Dickey Fuller (ADF) test, which reports the degree to which a null hypothesis can be rejected or not to determine whether our data are stationary or not. This is interpreted using a threshold of 0.05, which will tell us whether we reject or accept the null hypothesis. In the case of a non-stationary time series, the log scale transformation and the ordinary differencing transformation are used. The former can help to stabilise the variance of the series, while the latter helps to stabilise the mean by eliminating level shifts and thus reducing trend and stationarity. In addtion, the autocorrelation (ACF) and partial autocorrelation (PACF) functions will allow us to find out how many moving averages and autoregressives we are using in our model, respectively.

To introduce the predictive model, students need to understand the concept of a time series. A definition of a time series could be a series of independent variables as a function of time, where t indicates the time steps [29]. Furthermore, it is called stationary if the mean and variance are constant over time. However, it is very common that the mean and variance do not remain constant over time. In this case, the series is non-stationary and, therefore, unpredictable and difficult to model [30,31]. The ARIMA (AutoRegressive Integrated Moving Average) model is a time series forecasting method used to analyse and predict data points over time. It is a combination of autoregression, differencing and moving average components [32]. The analysis prepared with the students can be

Table 2
Predictive model assessment metrics.

ARIMA MODEL	RMSE	MAE	MPE	Ljung–Box Test
Temperature	0,3499	0,1240	−0,0065	0,9869
co2	55,8361	18,9220	−1,3299	0,8632
Humidity	0,6878	0,3163	−0,0021	0,2259
soilTemp	0,1528	0,0194	0,0021	0,2259
Light	1867,1170	264,5144	0,6467	0,8375

Table 3
Recommendations based on data the implemented predictive model (predictive analytics).

Variable	Thresholds	Scenario	Actionable recommendations for students and teachers
Temp.	< 20 °C	Low temperature	Heat the space using the AC system
Temp.	> 26 °C	High temperature	Cool the space opening the window or using the AC system
Humidity	> 70%	High ambient humidity	Close the window
Humidity	< 30%	Low ambient humidity	Use a humidifier
CO_2	> 1000 ppm	High density of CO_2	Switch the air purifier
CO_2	> 1500 ppm	Density of CO_2 is too high	Open the door
CO_2	> 2500 ppm	Density of CO_2 is extreme	Open window and door for cross ventilation
CO_2	> 600 ppm	Human in class	Hello and welcome to the classroom!
Light	< 500 lux	Very dark space	Raise the shutters or switch on the light system
Light	> 1000 lux	Very bright space	Lower the shutters or dim the light

found in Appendix A.1. Here, only the model equation is shown directly for a seasonal data series:

$$\Phi_P(B^s)\phi_p(B)(1-B)^d(1-B^s)^D = \theta_q(B)\Theta_Q(B^s)\epsilon_t \quad (1)$$

The notation of Eq. (1) is described as follows: p is the order of the autoregressive part; d component indicates the number of differences needed to achieve stationarity; and q is the order of the moving average part; P represents the number of autoregressive lags for the seasonal component; D is the number of times the seasonal data needs to be differenced to achieve stationarity; Q is the number of lagged forecast errors for the seasonal component, and s is the seasonal period.

3.2.2. Results

This case study has resulted in a predictive model that reliably anticipates CO_2, temperature, and humidity variables. Appendix A.2 shows the forecast of each of the variables in a short time interval (1 day). Consequently, the avatar can be configured with action recommendations on this time frame. Table 2 shows the error measures of the training set: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Percentage Error (MPE), and the result of the Ljung–Box test in order to check the model fit. It is worth noting the high RMSE value of the light variable, which confirms that it will be the most difficult variable to predict accurately with the ARIMA model. The rest of the RMSE values, including the CO_2 level, are acceptable and correspond to the choice of the best possible model.

According to the Ljung Box hypothesis, as long as the p-value exceeds the value of 0,05, we have white noise and, therefore, the null hypothesis H_0 is not rejected, which means that the residual values are normally distributed. This is true for all the variables and thus the model is valid.

3.2.3. Conclusions

This case study shows that it is possible to estimate each of the predicted variables in the short run, thus adding artificial intelligence to the initial setup. Hence, the avatar can anticipate specific scenarios with key recommendations towards environmental awareness in the classroom moderating energy consumption, and alerting unhealthy conditions for plants and humans. Table 3 describes the recommendations configured based on existing regulations for lighting [33], ventilation [18], and the use of heating/air condition in public buildings [19].

Two main limitations constrained this study: First, the data sample comprises a relatively short period of time (three months in spring semester), in a specific classroom, and lectures. This predictive model might obviously differ considering a different physical learning space, with different number of students and different lecture schedules. Second, power and WiFi outages caused jumps in data collection resulting in non-stationary series. Therefore, appropriate transformations were performed on the data sets.

3.3. Case study 3: Beyond senses and sensors. Using plants to identify human activity and emotions

The third case study was conducted in the context of postgraduate studies. Here, the focus was on exploring the potential of plants for identifying human presence, activity, and emotions using machine learning techniques. This groundbreaking research revealed the possibilities of utilising plants as sensors for understanding human behaviour and emotions in learning environments.

In a series of projects starting in 2019, we have correlated voltage differentials in plants between leaves and roots with human movement and sound. Using the plant spikerBox, we measured correlation between human emotions and mimosa pudica and basil,

Fig. 8. (a) Measuring the impact of Eurythmic gestures on garden plants using the spikerbox. (b) Measuring the emotions of Jazz musicians using the plant spikerbox connected to a basil plant during the concert.

as well as between eurythmic movement and lettuce, beetroot, and tomato plants. In addition, we also measured the response of the dancing plant (codariocalyx motorius) and tomato plants to sound.

In the first project, seven individuals were walking by a mimosa pudica in a meeting room, while the voltage differences between roots and leaves were measured with a plant spikerbox [34]. Resulting voltage patterns were converted to mel frequency cepstral coefficients (MFCC) and then correlated with binary emotions (sad, happy) of the people walking by, labelled by two raters. Using a random forest machine learning algorithm, human emotions could be predicted from the voltage differentials with an accuracy of 66%.

In the second experiment, garden plants such as lettuce, tomatoes, and beetroot were exposed to eurythmic dancing [35]. Again computing the MFCCs of the voltage differentials measured with the plant spikerbox, we found significant correlations of up to 65% between the hand movements of a eurythmic dancer and the voltage differentials of lettuce, tomatoes, and beetroot. The hand movements of the dancer were categorised using automatic image recognition. Fig. 8.a illustrates the data collection process of the eurythmic dancer using the spiker box connected to beetroots.

The third experiment compared the voltage changes of the dancing plant (codariocalyx motorius) with sound exposure of the plant in ten second intervals of pure sounds of frequencies of 200 Hz and 600 Hz [36]. Again MFCCs were computed and correlated with the sounds by mean, variance, interquartile range, Hjorth Mobility, Kurtosis, Skewness, DFA, Hjorth Complexity, and Hurst Exponent, as well as using an MLP classifier resulting in an accuracy of 72%. It was thus found that the plant perceives sound in its environment and shows this reaction in the electrical signal. A second sound experiment measured the response of tomato plants to human voices [36]. Tomato plants were alternatively exposed to a children's choir, and the reading of ebooks. Using a CNN classifier on the MFCCs, an accuracy of over 60% was achieved in distinguishing between these two conditions.

In another project, 72 students were watching 15 video snippets with emotionally moving content, while their emotional facial expressions were captured with video cameras and the plant spikerbox connected to a basil plant [37]. Computing MFCCs of the plant spikerbox output, and comparing them with an emotion classifier categorising seven different emotions (joy, sadness, disgust, surprise, anger, fear, neutral) led to an accuracy of 34% using a ResNet classifier, which is significantly above the baseline of 14.3%.

The last project compared the emotions of a jazz orchestra with 19 musicians, tracked through their facial expressions, with the MFCCs of the spikerbox readings of a basil plant [38]. Using the three emotions angry, sad, and happy from the face emotion recognition system as the ground truth, we obtained prediction accuracy of 69% using the XGboost machine learning algorithm. Fig. 8.b shows the measurement setup using the plant spikerbox connected to four basil plants as biosensors during the live concert.

We are currently working on an extensive project with the plant spikerbox, where the goal is to measure and improve teamwork by correlating emotions of human teams with electrical signals of plants tracked with the plant spikerbox.

3.3.1. Methods

We used the plant spikerbox to measure collaboration quality among 87 Master students, who were working together for the duration of one week in 22 teams on a week-long group task. The physical setup consisted of a large hall, where each team was sitting and working together around a table separated by movable white boards from the other teams (see Fig. 9). On each table there was an individual 360-degree camera that recorded videos of all participants sitting around the table. A dedicated conference microphone collected the discussion of the team members. The purpose of using the microphone was not to capture content, but to measure emotions from audio. On each group table there was a plant spikerbox connected to a basil plant with the goal of recording the mood of the participants. As the dependent variable of collaborative performance, we used both individual and group level success metrics. On the individual level, we asked each participant to report their wellbeing using the well-known PERMA

Fig. 9. The setting for using the plant spikerbox to measure collaboration. The left picture shows the entire lecture hall with the 22 group tables separated by the white boards. Two operators of the recording system were running a dashboard to check the cameras and plant spikerboxes. The centre picture shows an exemplary group table equipped with 360-degree camera, conference microphone, and basil plant connected to a plant spikerbox. The right picture shows the aggregated success metric PERMA for the four active course days.

metric from positive psychology [39]. PERMA stands for Positive emotions, Engagement, Relationships, Meaning, and Achievement. PERMA measures were taken daily by asking the participants to fill out a survey [40]. Group level metrics were taken on the last course day, where each team had to present their results, which were rated both by peer ratings and by the instructors.

3.3.2. Results

We collected data on four out of the five course days, on the first day there was no teamwork, as the teams were busy choosing a topic for their group task. We also collected video recordings and audio recordings of the entire collaboration period, plus the spikerbox wav files, resulting in a huge amount of data. Currently, we are in the post processing phase, we have analysed all the audio and video data, and computed files that show the aggregated emotions of all participants according to the Ekman emotion framework [41]. Ekman distinguishes six basic emotions fear, sad, anger, disgust, joy, and surprise, we added an additional emotion "neutral", which was added to increase the accuracy of our machine learning model. This analysis led to a time series file containing the average likelihood for each of these seven emotions for each of the 22 teams at each second for both video and audio [42,43]. These emotions were then compared to the plant spikerbox output. Using the plant emotion prediction model developed in an earlier project [37] gives an accuracy of 0.324 which is clearly better than the 0.143 which could be randomly obtained. The best results of this early model were achieved using MFCC based CNN and Dense classifiers [37]. As the spikerbox gives a sample rate of 10'000 samples per second, the spikerbox output had to be downsampled. Experimenting with different machine learning models resulted in the best one using one dense layer with 1024 neurons, one dropout layer and another dense layer with softmax activation on top of the ResNet50 feature extractor. We are currently working on building a new model to achieve higher plant prediction accuracy for the Ekman emotions mentioned above.

3.3.3. Conclusions

Our plant spikerbox experiments have just scratched the surface of the emergent field of using plants as sensors of human emotions, and much further work is necessary. Nevertheless, our different experiments have shown that using plants as biosensors measuring hard-to-compute human characteristics such as emotions opens up new avenues of using plants in educational smart environments.

4. Discussion

In this article, we presented an AIoT (Artificial Intelligence of Things) system specifically designed for learning contexts, targeting the fundamental functions of smart learning environments: sense, analyse, and react [44]. The AIoT system seamlessly integrates sensors, visual and auditory interfaces, and intelligent algorithms to collect data, analyse patterns, and provide actionable recommendations, thereby enhancing the learning experience for students and teachers. The system showcased in this article (and illustrated in Fig. 10) offers an approach to understanding and optimising learning environments. By employing a range of sensors, including those measuring variables such as CO_2, temperature, humidity, and light, the system effectively captures data about the indoor learning space (cf. chapter 3.1). This data collection enables an in-depth analysis of the environment's appropriateness for learning, taking into account factors such as well-being, attention, and learning performance [45]. Our AIoT system emphasises naturalising learning spaces with the presence of plants (cf. [46,47]). Plants offer numerous benefits in educational settings, from enhancing air quality to promoting a sense of calm and connection with nature. To explore the relationship between plants and humans further, the AIoT system integrates sensors within plants, collecting information about their state, such as temperature and electrical activity. This enables investigations into how plants respond to human stimuli, including presence, movement, and noise. Our third case study indicated a promising correlation for detecting and evaluating plant responses (cf. chapter 3.3). In essence, the system views plants not only as subjects of study but also as active participants in the learning environment. However, further research into this topic is needed.

To facilitate interactions within learning contexts, the AIoT system incorporates various interfaces. Visual actuators, such as coloured LEDs, and an OLED screen, serve as visual representations of the collected and analysed data. These visual cues allow users,

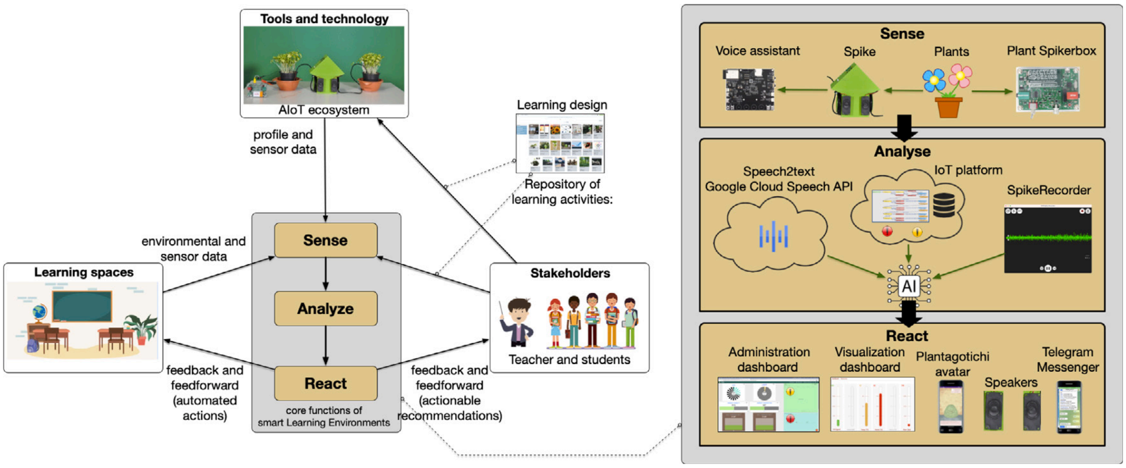


Fig. 10. An AIoT model for Smart Learning Environments.

both students and teachers, to observe and interpret the information in intuitive and meaningful ways in real time. Additionally, an avatar named Plantagotchi has been programmed to provide personalised recommendations for ideal conditions of well-being and health for both plants and people in the learning environment (cf. chapter 2.5). This interactive avatar engages users, guiding them towards creating an optimal environment for learning and promoting a holistic approach to education. Furthermore, the AIoT system includes a voice assistant that enables seamless interaction between users and the system, allowing teachers and students to inquire about the current state of the plant and its historical data over specified time ranges. This voice-based interaction offers a natural and intuitive way for users to interrogate the AIoT system, fostering effective communication and promoting active participation in the learning process. In addition, the AIoT system incorporates a mobile text bot based on the Telegram platform. This text bot keeps users informed about the telemetry data collected by the sensors and facilitates discussion groups for collaborative analysis among classmates and educators. Our interactive platform promotes knowledge sharing, encourages collaboration, and creates a vibrant learning community, where students can engage in meaningful discussions and deepen their understanding of the collected data in connection with environmental education.

Working with the plant spikerbox takes these educational aspects even further. While many plant lovers like to talk to their houseplants, they do so without scientific backing, as the science of making interaction with plants measurable is still at very early stages. The plant spikerbox provides a tool for measuring voltage differences in plants as a response to external events, demonstrating that a plant is not just a static object, but a living organism that perceives and reacts to external stimuli. In that regard, our experiments continue where Jagadish Chandra Bose, the pioneer of plant measurement, started off at the beginning of the twentieth century [48], measuring electrical responses of mimosa pudica and codariocalyx motorius to external triggers. Already, Bose said that plants have life and "*that everything in man has been foreshadowed in the plant*" (ibid.).

The approach being taken in our three case studies is one of holistic situated and personalised learning. This involves several parameters and actors. Firstly, teachers and students sharing an indoor space with specific learning objectives in mind. Secondly, curricular targets that need to be addressed through a variety of teaching/learning scenarios and learning activities in a personalised and perhaps gamified way. Thirdly, indoor plants suited to interact positively with the ambient environment in order to generate a healthy learner/teacher-friendly atmosphere supporting concentration and learning performance, while at the same time also taking the role of an interactive learning object. Finally, the AIoT technology that monitors, communicates and mediates between the other three agents in an easy to understand way. Nonetheless, it should be noted that the AIoT system presented here might be complex to use for teachers with an average digital competence. Teachers in case studies 2 and 3 required technical support from the researchers to configure the system correctly.

This work demonstrates how artificial intelligence can add value to IoT in diverse learning contexts, with increasing levels of complexity, as illustrated in the presented case studies. In the first case study (cf. chapter 3.1), primary school students engage in environmental awareness through notifications presented in visualisation dashboard. These alerts inform them of inappropriate scenarios and provide tailored advice to prevent unfavourable outcomes for both plants and humans. In the second case study (cf. chapter 3.2), a predictive model is designed using data collected over three months from a university classroom. This model effectively anticipates reliable recommendations about specific environmental (and plant) variables with a one-day lead time. This achievement involves intricate data analysis techniques to configure alerts and actionable recommendations via the Plantagotchi (cf. chapter 2.5), which employs a lizard metaphor, or via the voice assistant (cf. chapter 2.4) which employs speech recognition features (speech-to-text and text-to-speech) to naturalise the interaction with the system. Lastly, in the third case study (cf. chapter 3.1), complex machine learning algorithms are employed to explore how plants react to human behaviours and emotions, focusing on master's level students working in groups. These applications underscore the versatility and potential of artificial intelligence in reshaping learning environments. This work has investigated AI algorithms towards individual recommendations for action (i.e., Table 3) in classrooms. Future research might further investigate how AI can support IoT exploring collective behaviours (as presented in chapter 3.3) and social interactions [49] to anticipate recommendations targeting group decision making [50].

The overall framing of the development of the presented ecosystem is situated within the theme of environmental education and strengthening environmental awareness among the next generation, combined with the promotion of essential digital skillsets that characterise the 21st century information society. Depending on the level of education the students are in, different subject specific competence-oriented hands-on activities can be designed using the AIoT. It emerged from our three case studies that AIoT facilitates the personalisation and gamification of the system's curricular components. Additionally, our approach of technology-supported biosystems in indoor learning spaces confirms previous studies regarding the benefits of plants on healthy ambient conditions in support of learning and well-being. In this manner, the triangulation of our pilots leads us to believe that the AIoT system holds a lot of potential in educational settings that can be applied across various subject areas.

The three case studies presented in this article contribute to our understanding of the practical implementation of the AIoT system in different educational contexts. The findings highlight the positive impact of the system on various aspects of education, including environmental awareness, personal well-being, digital competence and the dynamic relationship between humans and plants. The results of our pilots confirm the suggestion that integrating artificial intelligence in the Internet of Things as AIoT carries many potential benefits for competence development in education.

CRediT authorship contribution statement

Bernardo Tabuenca: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Manuel Uche-Soria:** Conceptualization, Data curation, Formal analysis, Investigation, Validation, Writing – original draft, Writing – review & editing. **Wolfgang Greller:** Funding acquisition, Writing – original draft, Writing – review & editing. **Davinia Hernández-Leo:** Conceptualization, Data curation, Formal analysis, Resources, Software, Writing – original draft, Writing – review & editing. **Paula Balcells-Falgueras:** Conceptualization, Data curation, Methodology, Writing – original draft. **Peter Gloor:** Data curation, Formal analysis, Writing – original draft, Writing – review & editing. **Juan Garbajosa:** Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Bernardo Tabuenca reports financial support was provided by Polytechnic University of Madrid. Bernardo Tabuenca reports a relationship with European Commission that includes: funding grants.

Data availability

Data will be made available on request.

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Appendix. Case study 2

A.1. Predictive model on ARIMA

Firstly, the autoregressive part is based on the idea that the current observation can be explained by past values. These models are denoted as $AR(p)$, where p is the number of samples that explain the data behaviour. Thus, an autoregressive model of order p can be written as:

$$AR(p) : y_t = \mu + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \epsilon_t \tag{2}$$

where $\phi_1 \dots \phi_p$ are the constant coefficients to estimate when training the model, ϵ_t is the white noise, and μ is the mean of the time series. Secondly, the moving average part consists of approximating the time series using only white noise. Assume that $\theta_1 \dots \theta_q$ are the parameters of the moving average component that need to be estimated, mathematically it is represented as shown in Eq. (3):

$$MA(q) : y_t = \mu + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t \tag{3}$$

Thirdly, the ARMA(p, q) model composes of Eqs. (2) and (3):

$$ARMA(p, q) : y_t = \mu + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \theta_1 \epsilon_{t-1} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t \tag{4}$$

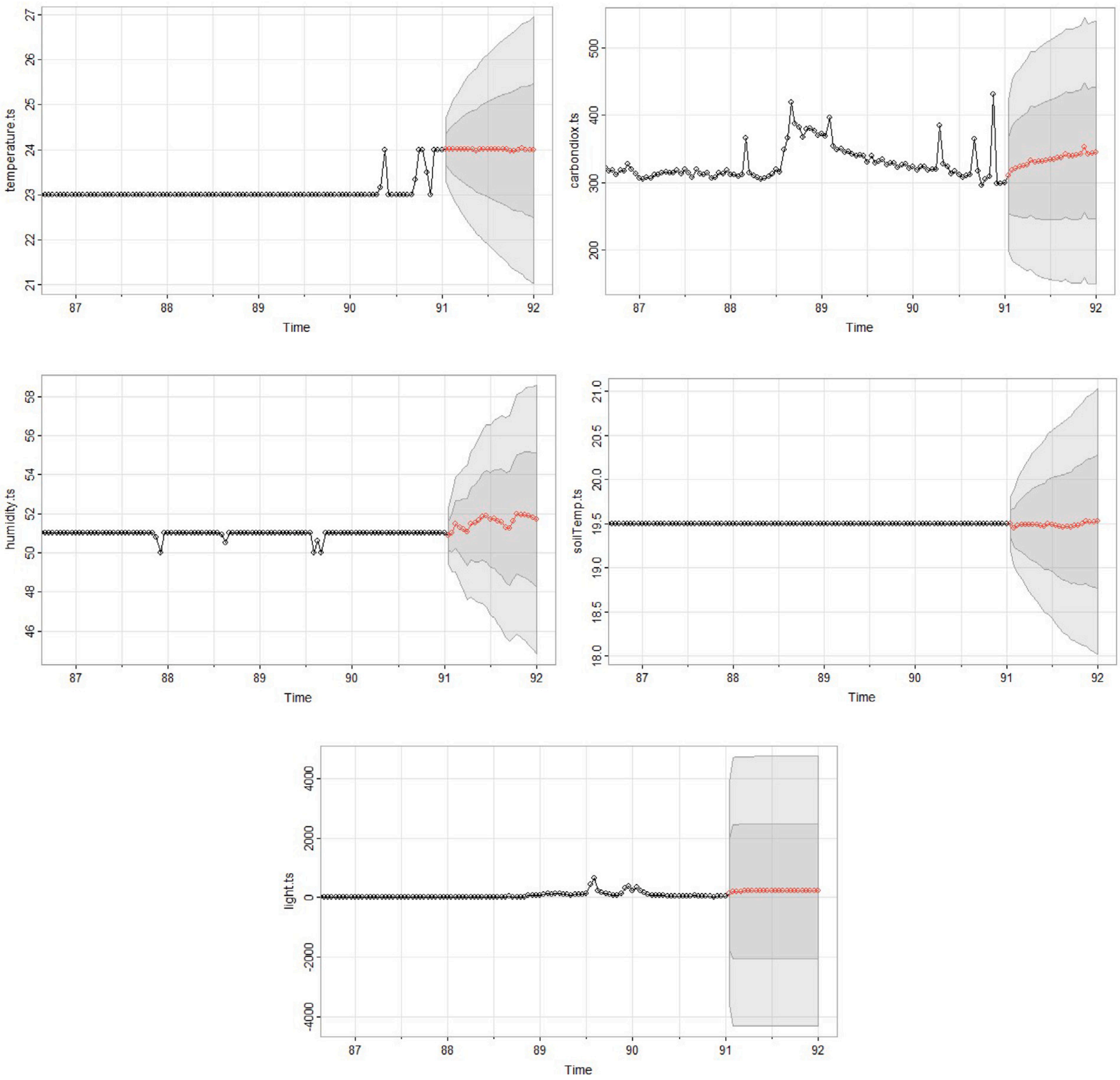

Fig. 11. Predictions made on each of the variables.

Finally, the ARIMA model is based on the assumption that the predicted value of a variable y_t is generated from a linear equation of a series of previous observations with random errors [51]. Then, combining autoregression, moving averages and differencing, we obtain the ARIMA(p, d, q) model:

$$y'_t = \mu + \epsilon_t + \sum_{i=1}^{p} \phi_i y'_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} \tag{5}$$

where y'_t is the differenced series (it may have been differenced more than once); p is the order of the autoregressive part; d component indicates the number of differences needed to achieve stationarity; and q is the order of the moving average part. However, for more complicated models, it is much easier to work with backshift notation ($By_t = y_{t-1}$). Thus, Eq. (5) can be written in backshift notation as:

$$\left(1 - \phi_1 B - \cdots - \phi_p B^p\right)(1 - B)^d\, y_t = \mu + \left(1 + \theta_1 B + \cdots + \theta_q B^q\right)\epsilon_t \tag{6}$$

θ, ϕ, p, ϵ, μ and q are represented in the previous equations. If the data exhibits seasonality, a seasonal ARIMA model, denoted as SARIMA$(p, d, q)(P, D, Q)s$, is used. The first term (p, d, q) describes the non-seasonal part and the second term $(P, D, Q)_s$ express the seasonal part of the model [52]. Mathematically it is represented as:

$$\Phi_P(B^s)\phi_p(B)\nabla^d(B)\nabla_s^D(B)y_t = \theta_q(B)\Theta_Q(B^s)\epsilon_t \tag{7}$$

The notation of Eq. (7) is described as follows: p, d and q are explained in Eq. (5), P represents the number of autoregressive lags for the seasonal component, D is the number of times the seasonal data needs to be differenced to achieve stationarity, Q is the number of lagged forecast errors for the seasonal component, and s is the seasonal period.

A.2. Predictions results

Fig. 11 shows the forecast of each of the variables in a short time interval (1 day).

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