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AGILEST approach: Using machine learning agents to facilitate kinesthetic learning in STEM education through real-time touchless hand interaction

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ABSTRACT

There is an increasing interest in creating interactive learning applications using innovative interaction technologies, especially in STEM (Science, technology, engineering, and mathematics) subjects. Recent developments in machine learning have allowed for nearly perfect hand-tracking recognition, introducing a touchless modality for interaction within Augmented Reality (AR) environments. However, the research community has not explored the pedagogical approach of Kinesthetic Learning or "Learning by Doing", hand tracking, and machine learning agents combined with Augmented Reality technology. Fundamentally, this exploration of touchless interaction technologies has taken on new importance in the new post-COVID world. Meanwhile, machine learning has gained attention for its ability to enhance personalized learning and play a vital new role as a virtual instructor. This paper proposes a novel approach called the *AGILEST* approach, which uses machine learning Agents to facilitate interactive kinesthetic learning in STEM education through touchless interaction. The first case study for this approach will be an AR learning application for chemistry. This application uses real-time touchless hand interaction for kinesthetic learning and uses a machine learning agent to act as both trainer and assessor of the user. The evaluation of this research has been conducted remotely through a usability study with expert reviewers, which includes 15 young researchers with peer-reviewed work in Human-Computer Interaction & AR and 2 subject experts STEM teachers at the secondary school level. The usability evaluation through NASA Task Load Index (NASA-TLX), Perceived Ease of Use (PUEU), and Perceived Usefulness (PU) with expert reviewers provide positive feedback about this approach for productive learning gain, engagement and interactiveness in learning STEM subjects.

Learning Technology is continuously evolving, and its importance is now being recognized worldwide due to the COVID-19 pandemic. As a result, most countries have adopted some form of remote learning during the outbreak's peak. The first country to do this was China which adopted the *Suspending Classes Without Stopping Learning Policy* [46], which examined alternative learning solutions that facilitate the use of technology integration in remote learning.

One area where remote learning suffers is naturally in hands-on experiments for STEM (Science, technology, engineering, and mathematics) subjects. However, with the development of new interaction techniques and intelligence, there are possibilities to support STEM subjects learning virtually. One approach is to use eXtended Reality (XR), which is an umbrella term for Augmented Reality (AR), Mixed Reality (MR), and Virtual Reality(VR) as explained in Fig. 1 and especially suitable for presenting information during experimentation, as it can be used to integrate both physical and virtual lab work [2].

By augmenting the real world with virtual objects, AR provides new possibilities for education in different educational contexts [23,45]. For example, in the learning process, student engagement is a critical component, and AR has been proven to be highly motivational for students to create more involvement in the learning process [38].

In the STEM subjects, instructors face many difficulties in the teaching process because students lack basic competency, motivation, background knowledge, encouragement, attention, confidence, and other aspects of a subject [7]. Kinesthetic learning ("learning by doing") or physical engagement with the learning process [40], when combined with AR, can create an engaging learning environment to develop technical concepts. To facilitate "learning by doing" or hands-on learning, hand-tracking technology can play a crucial role in virtual environments. These hand-tracking technologies are gaining new attention in the post-COVID world as a recommendation to avoid touching devices to prevent the spread of the disease [3].

AR education does not necessarily require expensive AR HMDs such as the Microsoft Hololens, an entry-level smartphone with a camera is more than capable of providing a basic AR experience, as demonstrated by the success of AR games like Pokémon GO. The vast majority of

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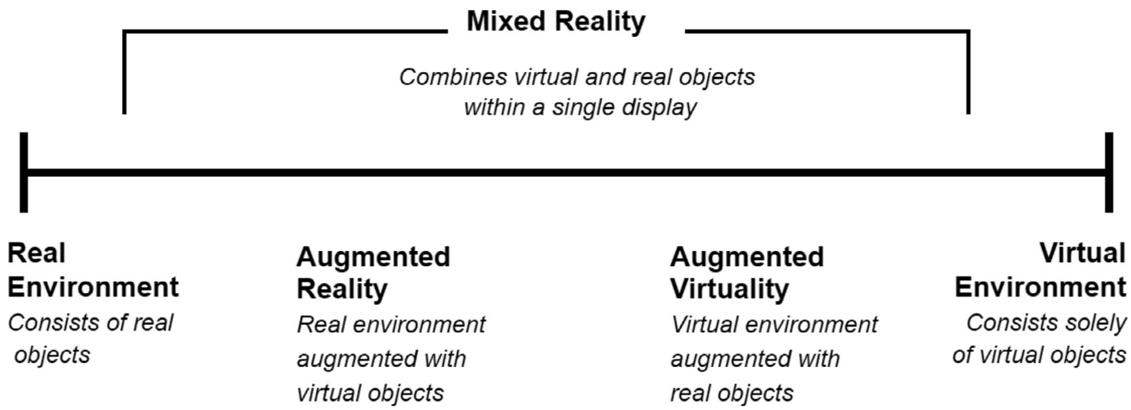

Fig. 1. Difference between Real environment, Augmented Reality, Augmented Virtuality and Virtual Reality explained by Reality-virtuality continuum [22].

smartphones are capable of some form of AR, and within the next few years, even the most inexpensive smartphone will have the capabilities of a current state-of-the-art smartphone. This technology can assist learning everywhere without any location or cost restrictions; thus, its accessibility makes it the perfect target for developing learning technologies of the future. In addition, several interaction techniques are explored in AR environments, including touch, marker tracking, gestures, and hand recognition [15].

By providing real-time hand interaction with virtual objects using smartphones, they facilitate an effective means of developing kinesthetic applications, which can be an effective and interactive way of learning. Furthermore, the use of inexpensive smartphones can be crucial in resource-constrained environments that can exist in less developed areas of the world or even in underprivileged regions in significantly developed countries [4,34]. It is impossible to provide learning materials in the classroom or personal learning space in these environments, restricting them from learning scientific concepts through hands-on practice. Thus, the case study application used in this paper incorporates the scientific topic of chemistry with a learning scenario of resource-constrained learning environments. A lesson aimed approximately at a middle/high school level allows for a virtual hands-on learning approach.

The principal contribution of this paper is the introduction of the AGILEST approach: Using machine learning AGents to facilitate Interactive kinesthetic LEarning in STEM education using a Touchless interaction. Fundamentally, this approach does not replace the teacher but gives them more agility in their teaching as they can fit themselves into the process at any point. AR tools should be there to augment and enhance a person's abilities, not to replace the person.

The core focus of this research is to address the needs of resource-constrained environments to teach scientific and technological concepts in STEM subjects at the middle and high school level using a kinesthetic learning "learning by doing" approach. Along with the touchless interaction with the virtual learning material, this project uses the machine learning agents in AR acting as both virtual teacher and assessor to allow such an approach to scale up across a classroom. Furthermore, by integrating touchless interaction (full interaction with 3D models, not just gestures) with virtual objects, learning scientific subjects in AR can become more affordable and productive.

1. Related work

In the different systematic reviews, there is impressive and result-oriented work reported in the field of augmented reality for learning, which is based on various aspects of learning goals including increasing engagement, reducing cognitive load, developing interactive contents[21], increasing motivation, educational inclusion[37] and contents authoring [13,42]. From collaborative learning to individualized learning in the personal space and from classroom to remote learning, AR has shown acceptance in the audience due to its close relationship with the real environment.

AR has proved its ability to increase the interactiveness of learning contents in STEM education, like in chemistry [24], Inquiry-based Learning of Physics [39], mathematics [1] and gesture-based anatomy learning [26]. TheKinesthetic learning approach tested in AR using Kinect device for learning mathematics by drawing graphs and patterns [6] and leap motion device used for web-based 3D geometry learning which helped students to learn in a better way but reported some usability and performance issues in the gesture-based interaction. A gesture-based interaction approach using leapmotion was adopted for the recognition of Arabic sign language, which proved up to 88% recognition accuracy [14]. Furthermore, a similar interaction approach was adopted for free-hand interaction in stroke rehabilitation [27].

These results have been strengthened by a recent study that reported on how increased performance of touchless gestures can be achieved in smartphone-based apps using color markers [36].

Agent-oriented approach in the AR [17] and the suitability of these agents [9] opens the opportunities to use agents to enhance learning achievements in STEM education and skill training. Use of these meaningful conversational agents has been reported to help students to perform peer assessments with reasonable accuracy in formal learning [28].

In chemistry, marker-based and screen touch interaction have been tested previously to provide interactive learning with virtual 3D models [20,29] and hands-on learning [44] which has reported growing interest and engagement of the students in terms of the interactive learning approach. The hands-on learning approach was also explored to find the effectiveness of learning by doing in virtual learning [11]. However, this interaction is limited to 2D screen touch or moving the markers to interact with the elements to learn chemistry. There are affordability and portability issues in the current context of hands-on learning as high-end HMDs are expensive to afford, and desktop systems are not portable if considering the leapmotion and Kinect real-time hand interaction.

New interaction techniques in AR, like gestures and especially real-time hand interaction, have added a new value to the interactive learning approaches in AR. For example, the potential of hand interaction for hands-on assembly tasks has been explored in PC assembly learning [5].

Artificial Intelligence (AI) & Machine Learning (ML) open new exciting opportunities and potential in educational practice when implemented as human-centered AI [47]. Ouyang and Jiao [33] differentiate the use of AI in education into three main paradigms.

- AI-Directed, learner-as-recipient
- AI-Supported, learner-as-collaborator
- AI-Empowered, learner-as-leader

Although previous research has made valuable contributions in developing AR applications for education, there has been little to no work

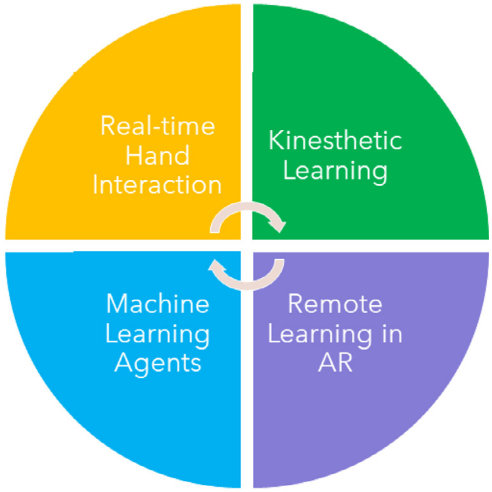

Fig. 2. Four major components of this research; Real-time hand interaction, kinesthetic Learning, Machine learning agents, remote learning in AR.

done exploring the use of virtual touchless hand interaction and intelligent agents within these systems. The possibility of meaningful AR-based agents [32] and kinesthetic learning in AR applications provide a vast opportunity to enhance the potential of AR technology in education (Fig. 2).

1.1. Research questions

RQ1: What are the possibilities of real-time hand interaction with handheld AR to increase productivity in kinesthetic (hands-on) learning?

RQ2: How virtual material in AR in the form of 3D can help to learn in resource-constrained environments using the hand interaction approach?

RQ3: Can machine learning play an influential role in immersive learning technologies for user training?

2. System design

To investigate the above-given research questions, this paper is presenting the AGILEST approach, which combines the use of Machine learning agents (using the Unity ML-agents plugin[1] [25]), real-time hand interaction by Manomotion[2] with ARFoundation. The overall system design architecture is explained in Fig. 3. This approach focuses on handheld devices (smartphones and tablets) to reach a wider audience. The following subsections will detail this approach, first in terms of machine learning, the touchless interaction implementation, and finally, outline the learning flow provided by this approach.

The design process translates the concept of touchless hand interaction and self-guided learning. Touchless (real hand interaction with virtual objects) technology in smartphones is the most recent advancement.

2.1. Machine learning agents

The AGILEST approach allows the machine learning agent to train the user about the chemical interactions using previously trained data. With ML-Agents, various training scenarios are achievable by collecting and recording different observations to make decisions, as explored by using reinforcement learning [10], explained in Fig. 6. This mediated agent-oriented approach helps the user learn which elements or molecules they will use to create different reactions. The Unity ML-agents plugin integrates machine learning agents within the system to achieve this goal.

Learning components of the ml-agent are explained in Fig. 4. Unity ML-agents plugin allows the creation of new or using pre-made environments for training agents to integrate into the unity application (As shown in Fig. 5). These agents use Python APIs to train the learning behavior.

To get the trained Neural Network (NN) models for integration in unity, hand interaction data of creating chemical reactions by completing multiple episodes. ML-agent collects observation of the the user's hand moves, picks, grabs, and creates reactions which lead to rewards by using functions of *CollectObservations(VectorSensor sensor), sensor.AddObservation* and *OnActionReceived (float[] vectorAction)*. To get better stability, this was tested over different sessions, and evaluated with different increasing buffer sizes shown in Fig. 6(ii) to achieve consistency (Fig. 7).

The use of agents within the AGILEST approach is twofold, as they are used for two aspects:

- End-User Trainer
- Self-Assessment

It follows the reward-based assessment using the errors and time-based data of the user's actions. (Fig. 8 shows the graphs of TensorFlow after training the data). According to reinforcement learning, the learning rate should decrease with time, as shown in Fig. 8. Finally, the ml-agent is trained on the same functions that the user will use in the next step (*TEST*) through hand interaction using the heuristic method.

2.2. Hand interaction

The Manomotion with ARFoundation framework enables hand tracking capability, which allows the user's hand to interact with the 3D objects through the smartphone camera.

This hand interaction is achieved using the depth API within ARFoundation. The custom-made hand is implemented by using hand tracking info to help the user locate the hand. When a user's tracked hand reaches any 3D object and collides, it activates the point light to notify the user that the interaction element is now interactable. Interaction allows the user to hold and move 3D cubic elements around to create a reaction of that chemical, as shown in Fig. 9 and Fig. 10. The application also reports the frame processing time and provides information about the different states of the user's hand (Grab, Hold, Drop).

After the reaction, the user receives audio feedback and vibrations telling them when these two chemicals react, what happens like *"When Hydrogen reacts with fire in the presence of air, it creates an explosion"*. Finally, the application records the time taken to achieve all the chemical reactions and sends the user to *QUIZ* module.

2.3. Learning flow

To understand how the machine learning agents and touchless interaction combine, the learning flow of the application needs to be examined. For machine learning agents, learning flow is following the concept of *AI-Directed, learner-as-recipient* and *AI-empowered, learner-as-leader* [33].

As seen in Fig. 11, the user starts with ***LEARN*** module, then goes to the ***TEST*** module and ends with ***QUIZ*** based assessment of user which reports the score of student back to Firebase database. In the ***LEARN*** module, the machine learning agent will take the previously trained Neural Network(NN) model to demonstrate to the user what possible chemical interactions are possible. Then, when the user feels they understand the possible interactions, they can move to the ***TEST*** module.

[1] https://www.unity.com/products/machine-learning-agents.
[2] https://www.manomotion.com/mobile-ar/.

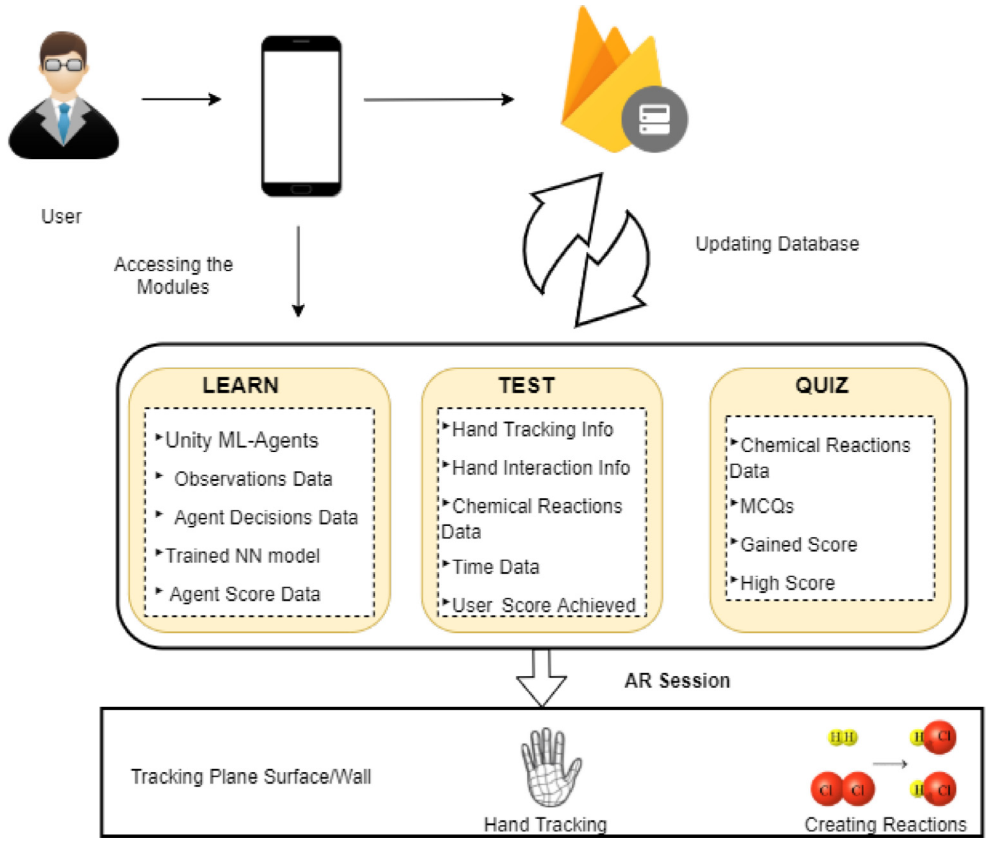

Fig. 3. System Architecture Diagram, explaining components of the system.

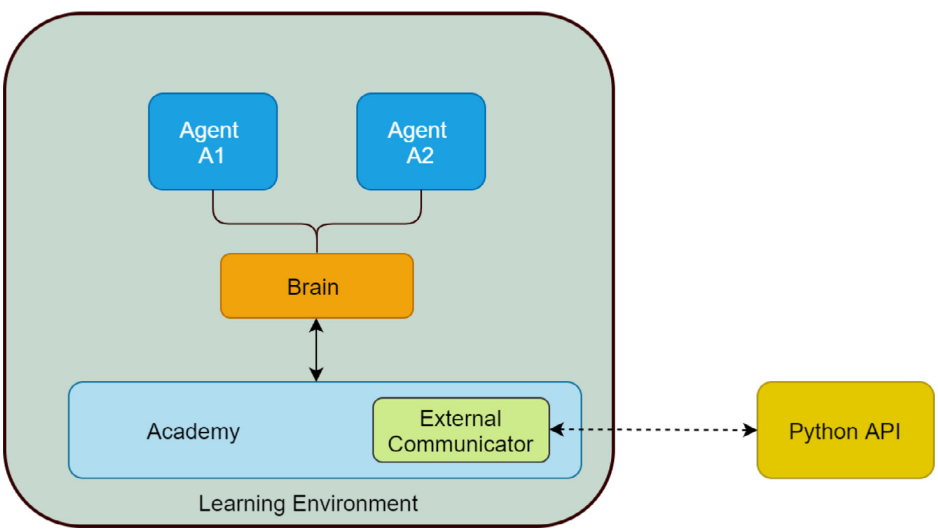

Fig. 4. Learning Component of the Unity ML-agents system, which explains how Python APIs work in the agent learning environment and train the agent's brain.

As per the AGILEST approach, the same NN model for training the user can be used for assessment to see how closely the user follows the previous agent's movements. It is achieved by feeding back the data to the NN model.

After completing the ***LEARN*** and ***TEST*** sessions, the user will move to the ***QUIZ*** module. The quiz questions are based on the chemical reactions users learned and tested in the previous two modules.

After completing the QUIZ, the application shows the user's score and compares it with the previous highest score. As per the complexity of the questions, each question has a different score and a different time limit to respond. Every wrong answer leads to a negative score. The final gained score of the user is shown on the screen, and a comparison of its score with the highest score achieved by other users is reported in the Firebase database.

Virtual laboratories for STEM subjects [35] are becoming a unique field in VR-enabled Education Tools. However, the additional requirements with display devices for tracking in AR add more complexity. And in terms of pure software engineering, using an agent-orientated abstraction could help in creating much more modular systems [19] that allow the separation of the display and tracking, making AR tutor-based applications much easier to develop. Combining this with an agent-oriented approach with Machine Learning (ML) can help to improve large-scale assessments and automate the learning process for more personalized learning [49] and technological transformation of remote education with AR/VR [31]. Yet, the user is not involved in the training process, he aims to learn from the trained agent in LEARN module and then move to "TEST" module, which is a practice module allowing kinesthetic learning in Augmented Reality. In an advanced

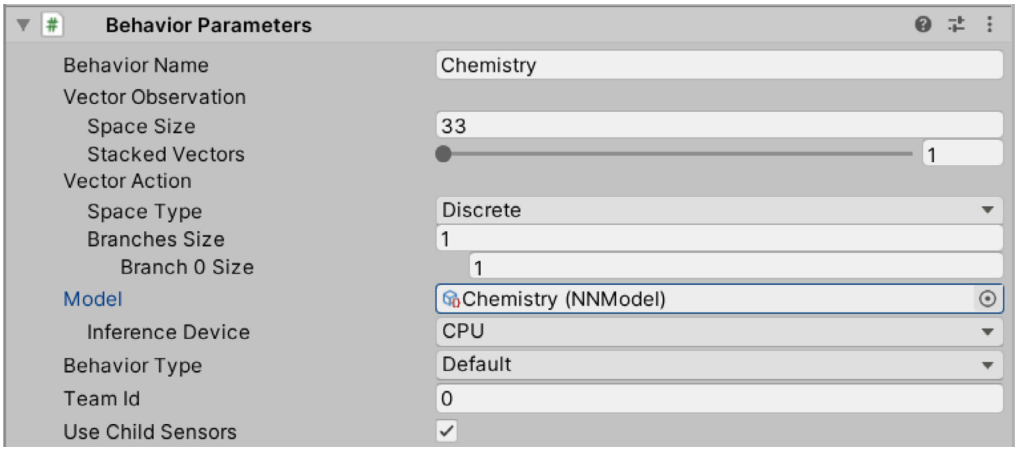

Fig. 5. Integration of trained Neural Network(NN) model after training.

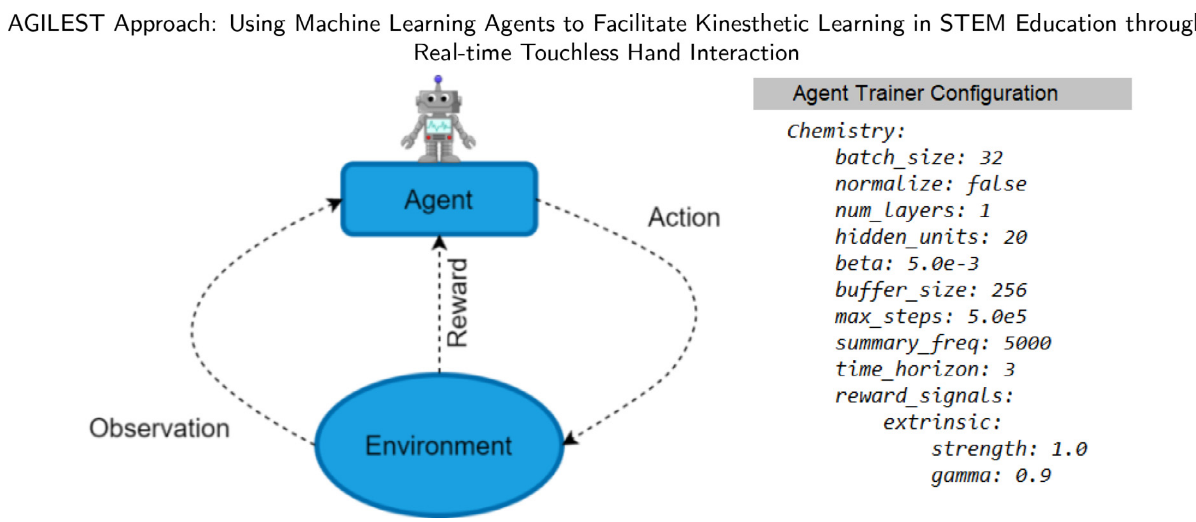

Fig. 6. (i) Process flow of ml-agent, following the reinforcement learning concept; (ii) Parameters used in the trainer configuration for agent training.

Fig. 7. (i) Learn module, trained with Machine learning agent (ii) Chemical Reaction explained.

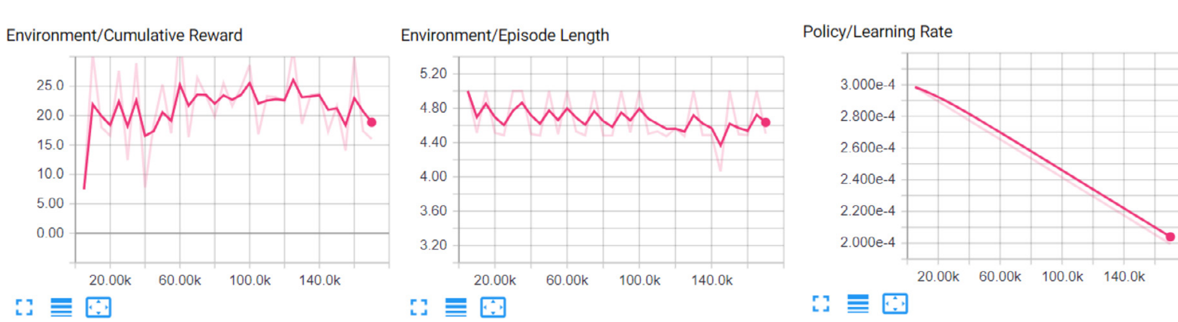

Fig. 8. Progress of the training agent. First graph shows the mean rewards with respect to the number of steps taken; the second graph is about the mean time taken to train each episode.

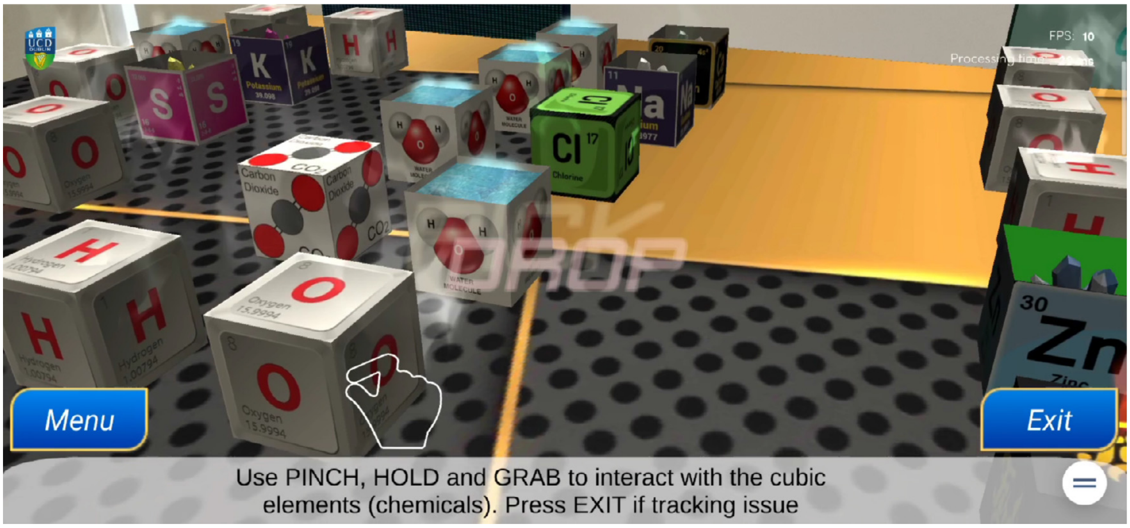

Fig. 9. When user's hand collides with any 3D cubic element, it allows grabbing and creating the chemical reactions.

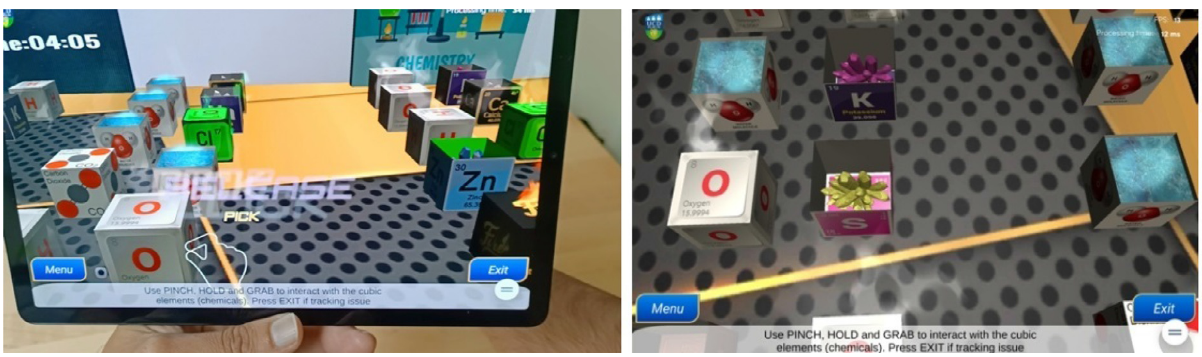

Fig. 10. User interaction with the application using tablet and visualization of elements with gas, fire, crystals, and liquid.

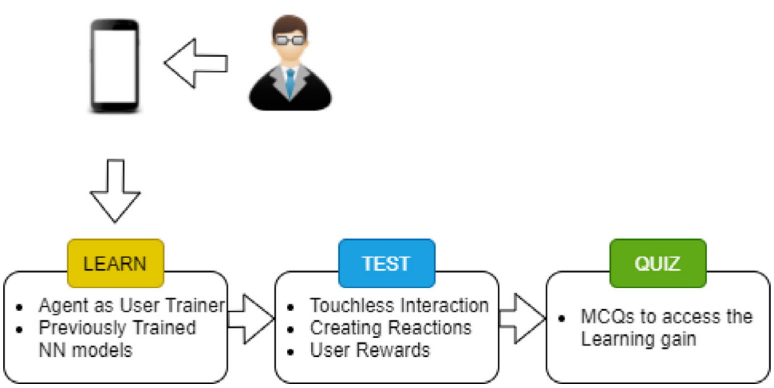

Fig. 11. Concept of learning flow with ML agent, hand interaction and MCQs quiz.

example, to develop a complex learning system, ml-agents can use live data to improve performance based on the data collected from different users during the learning process. This can be considered in future training application development in XR. The use of ml-agents or intelligent agents is very new in the immersive learning domain; in terms of pure software engineering, using an agent-orientated abstraction could help in creating much more modular systems that allow the separation of the display and tracking, making AR tutor-based applications much easier to develop. As this technology will go within immersive learning, it will better differentiate between scripted agents and trainer agents.

3. Evaluation

For conducting evaluations, many ethical, accessibility, and hygiene issues emerged due to COVID-19, especially where end users are under 18 [43]. This whole situation in the EU region made it impossible to get ethics approval for conducting experiments with the actual end-users under 18. As an alternative solution, studies with human factors involving machine interaction, especially those under 18, have adopted system evaluations with expert reviewers.

The experimental design of this research evaluation has adopted expert reviews method influenced by different Human-Computer

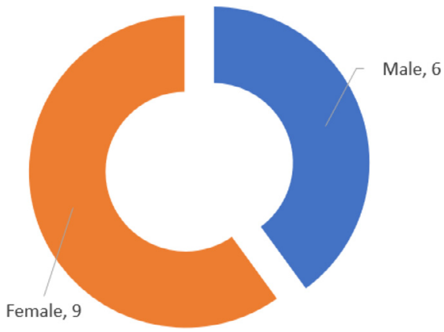

Fig. 12. Gender-wise distribution of the expert reviewers.

Interaction (HCI) studies for testing new applications involved with human factors [16,41,48]. This evaluation aimed to test the usability of interaction hand, adopted approach kinesthetic learning approach and efficiency of the machine learning agents in the augmented environment & getting feedback.

3.1. Participant recruitment

The participants were recruited through online conferences of Connected Learning Summit (CLS21)[3] & International Conference of the Immersive Learning Research Network (iLRN 2021)[4]. Out of 46 potential experts outreached via formal invitation emails, 19 expert reviewers signed consent to participate, and four withdrew later due to compatibility issues with their devices. Among 15 participating subjects, 6 were males, and 9 were females (Fig. 12.

All participants had research-level experience in eXtended Reality(XR) as general, interaction design, and learning technology with published peer-reviewed research papers. Fig. 13 shows the demographics of the expert reviewers which represents the diversity and inclusion of different regions in the concept and design evaluation process. To consider the subject experts' knowledge about the adopted approach and their involvement in the design improvement process, we engaged two STEM Teachers with having minimum 2–4 years of experience in teaching science subjects at the secondary school level. These subject experts have been engaged during EATEL Summer School on Technology Enhanced Learning[5] organized by the European Association of Technology-Enhanced Learning (EA-TEL) conducted in-person. Reviews of subject experts are discussed in the Section 3.5.

3.2. Evaluation procedure

Initial email-based outreach was performed as an invitation to get consent from young researchers in Human-Computer Interaction (HCI) and AR/VR based on their peer-reviewed work in the domain. After confirming their consent, these participants were provided with the APK for installation on Android smartphones, instructions to follow, Youtube video[6] explaining the application working. As a final step, all of these participants were provided with a questionnaire in Google form was provided to fill out after testing the application.

3.3. Tasks

The experiment consisted of installing AR application (presented above) on compatible Android phones and testing its usability, which includes the role of the machine learning agent as a trainer and real-time hand interaction to create chemical reactions using 3D cubic elements. The post-experiment task includes filling out a questionnaire which was designed using NASA Task Load Index [18] reported as one of the best tests to measure the cognitive load in AR [8], Perceived Usefulness and Ease of Use [12] to examine the usability & subjective questionnaires to get qualitative feedback.

NASA Task Load Index (NASA-TLX) is an assessment method to measure and conduct a subjective Mental Workload (MWL). It involves six factors.

- Mental Demand: Mentally demand needed for task completion?
- Physical Demand: Physical demand needed the task completion?
- Temporal Demand: Time demand and pace of the task?
- Performance: Success in accomplishing the task
- Effort: How hard to accomplish your level of performance?
- Frustration: How irritated, stressed, and annoyed felt to complete the task?

Following the Technology Acceptance Model(TAM) as shows in Fig. 14, the Perceived Ease of Use(PUEU) and Perceived Usefulness(PU) questionnaire were used to measure these human factors for acceptance of new technology.

- Perceived usefulness
- Perceived ease of use
- Behavioral intention

3.4. Results

An analysis was performed based on the questionnaire filled out by the participants after testing the application. Based on the data collected in the questionnaire, Tables 1 and 2 provide information about the mean, median, and high to low scores on usability and efficiency of real-time hand interaction and machine learning agents.

The graph in Fig. 15 shows the visual representation of results from Table 1.

The physical task load and effort needed to complete the task are lower than mental effort. Therefore, the time pressure to complete the tasks is also lower than all other factors.

Performance indicators are higher, and the score of mental frustration factor (cognitive load) to understand the system the first time is also a little higher, which is further explained in the Section 3.5 with user follow-up interviews. The PUEU graph in Fig. 16 indicates the effectiveness of hand interaction and machine learning agent is higher as compared to all other factors. The satisfaction level of the expert reviewers is very high regarding the general usability, and behavioral intentions of the user towards the system also indicate a higher score.

3.5. Follow-up interviews: User experience

Along with NASA and PUEU, there was a subjective questionnaire to understand user experience and get more detailed answers in the form of recommendations. During the first usability test, reviewers reported constructive experimental feelings regarding hand interaction and the use of ML-agents. In addition, responses were very positive about the system's consistency and usability. However, the common issues reported related to frame processing speed on different APIs like a user of *"Samsung S7"*.

Some responses of the experts on a general usability question were;

- *"felt some troubles for initially following the LEARN section, but the general interaction with the app and with cubic elements is easy after a few tries"*.
- *"it was not working with my phone, but I used a tablet. Previously, I played with gesture-based interaction with Hololens but this direct hand interaction is fantastic."*

[3] https://www.2021.connectedlearningsummit.org/.
[4] https://www.immersivelrn.org/ilrn2021/.
[5] https://www.ea-tel.eu/jtelss22.
[6] https://www.youtube.com/watch?v=mQ6D6ItJaG8.

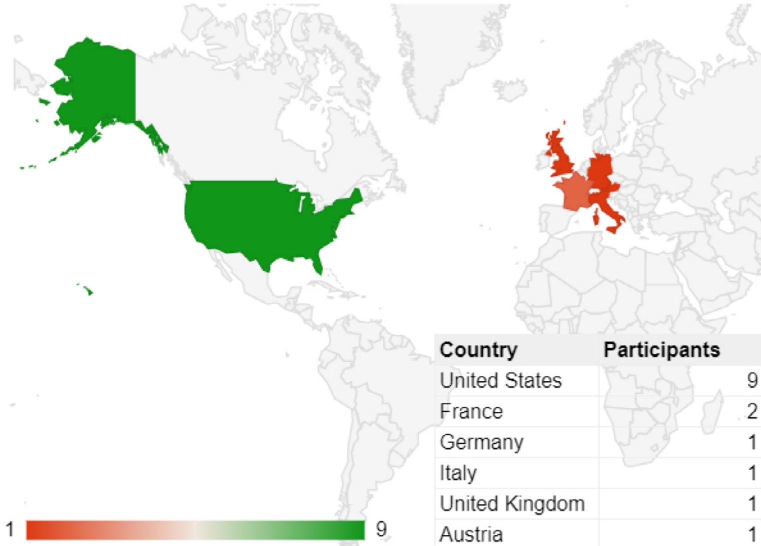

Fig. 13. Geographic mapping of the expert reviewers.

Table 1
Data of NASA Task Load Index questionnaire responses with average, median, min and max.

Questions- NASA Task Load Index 5-point Likert scale	Average	Median	Min	Max
1. How much mental and perceptual activity was required? (Low - High)	2.5	3	1	3
2. How much physical activity was required?	2.5	2	1	4
3. How much time pressure did you feel due to the pace at which the tasks or task elements occurred?	1.8	1	1	5
4. How successful were you in performing the task?	2.75	3	2	5
5. How hard did you have to work (mentally and physically) to accomplish your level of performance?	2.3	2	1	4
6. How irritated, stressed, and annoyed versus content, relaxed, and complacent did you feel during the task?	2.6	3	1	4

Table 2
Data of Perceived Usefulness and Ease of Use questionnaire responses with average, median, min, and max.

Questions - Perceived Usefulness and Ease of Use) 7-point Likert scale	Average	Median	Min	Max
1. Does the use of touchless hand interaction with 3D learning material improve learning performance?	5.2	6	1	7
2. Does using AR-based interaction method willenhance learning effectiveness?	5.6	6	2	7
3. Machine Learning module helps to learn creating chemical reactions.	4.78	5	2	7
4. Was it easy to learn chemical reactions with AR Hand Interaction?	4.6	5	1	7
5. Was it easy to interact with the App?	4.66	5	1	7
6. Was it easy to follow the Learn Module?	4.35	4.5	2	6
7. Was it easy to interact with the 3D chemicals with hand interaction?	4.06	4	2	6
8. I am satisfied with the learning approach and interaction.	4.6	5	2	7
9. I will recommend it to my students or friends.	4.66	5	1	7
10. Was it pleasant to use it?	5.06	5	2	7

As recommendations to make the app more productive, participants responded as;

- *"adding more learning material on different topics in the app can help to make the application more productive"*
- *"using spheres instead of cubes"*
- *"improving the machine learning part to create more attention"*.
- *"adding more learning material on different topics in the app can help to make the application more productive"*
- *"using spheres instead of cubes"*
- *"improving the machine learning part to create more attention"*.

A participant appreciated the visualization of effects relevant to the actual chemicals as, *"On top of the cubic elements, you can actually see the physical appearance of certain elements (e.g. gas flow, vapor, etc.)"* which is supposed to create more realism in virtual learning.

When it comes to the "most interesting part of the application", responses were;

- *"the most interesting concept was the indication of the hand actions that appear to be highly responsive to the actual human hand action"*
- *"educational part of AR chemistry"*
- *"hand interaction capability is my smartphone"*

The participants responded differently to the machine learning module to assist users in learning. Responses like *"this concept could be successful in this regard"* and *"yes, I think this needs more of a built-in lesson or learning goal. How is the AR activity allowing people to apply newly learned knowledge, or are they discovering new knowledge which will be formalized in a reflection? You may want to look at Kolb's model of experiential learning"* bring an overall conclusion that machine learning can help in AR learning when used as a pre-trained learning module. As a result of presenting the application to the subject experts, we collected their feedback about the learning flow, chosen case study for chemistry, and how it can improve the students learning. Overall, the experts showed very confident and exciting feedback for using hand interaction for "hands-on learning" and adopting machine learning agents to train end-users. The subject experts suggested adding more elements on for engaging the user in the process, adding more visual effects to represent elements, and allowing more space for the user in the virtual environment. The

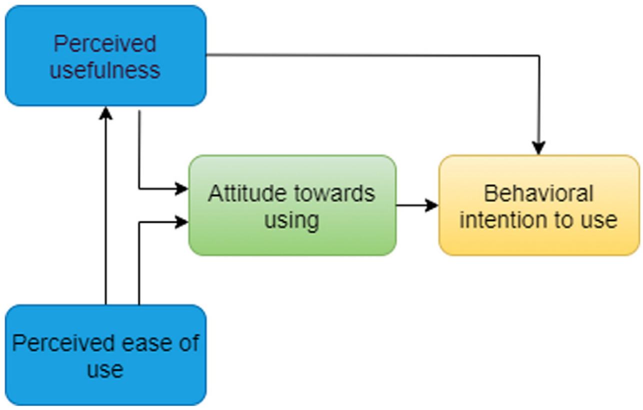

Fig. 14. Technology acceptance model [30].

successful implementation of the real-time hand interaction capability with the virtual objects over the real environment and user training capability using machine learning agents provided answers to RQ1, RQ2 & RQ3 of possibilities of combining these elements in an AR learning system, effectiveness on the kinesthetic activities in the immersive learning and increase in the engagement factor to motivate the learning.

3.6. Limitations

Due to remote experimental design, metrics used, and device compatibility, we acknowledged that our results might have limited generalizability. The evaluation strategy of expert reviewers instead of end-users (students) was adopted due to ethical issues because of the COVID-19 pandemic which restricts access to the end-users. The experimental study is about the assessing the performance of the system, feedback of the expert reviewers on usability, level of engagement created by this approach to motivate users, and advice of subject experts on subject-specific matters. Due to the lack of control group experiments, this paper is not presenting any comparison with traditional learning, use of hand interaction in AR, and the use of machine learning agents with the AR system.

As the app was designed for Android only, there is also a limitation for iOS users. However, the most critical technical limitation is the required API 24 (Android 7) or later, which means Android phones were assembled after 2016. Hand interaction in smartphone AR enables direct interaction with virtual contents, but as compared to the smartphone's field of view, human hands can ergonomically move in a broader range, requiring users to be aware of the usable interaction region. Therefore, the orientation of the application is set to landscape orientation by default because a wide field of view is necessary for better hand interaction.

The evaluation study and feedback collection were completed with expert reviewers who already have a good level of using AR applications so that actual end-users might face other usability and interaction-related issues.

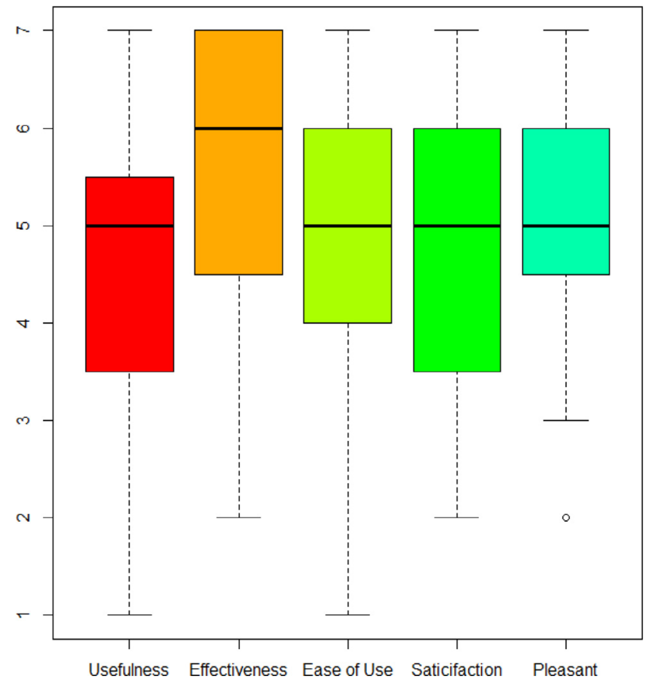

Fig. 16. Ratings for Perceived Usefulness and Ease of Use on 7-point Likert scale.

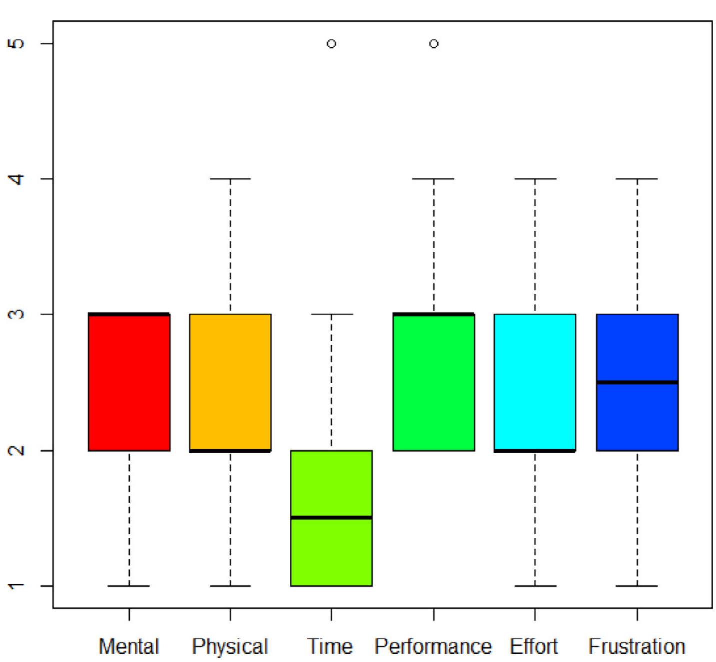

Fig. 15. Ratings of NASA Task Load Index (TLX) on 5-point Likert scale.

4. Conclusion and future work

The AGILEST approach has been introduced in this paper to demonstrate how touchless hand interaction and machine learning agents can be combined to develop intelligent learning environments for STEM education. Integrating ML-agents both as end-user trainers and as a facilitator for self-assessment is a novel approach that would allow the application to support learning in STEM subjects. Furthermore, Section 3.1 demonstrates how neural networks can be trained to mirror hand movements & interaction for kinesthetic tasks.

This work aims to provide teachers with more agility in their teaching and promote hands-on learning in resource-constrained environments. The usability tests conducted with the expert reviewers have shown that hands-on learning in smartphones using virtual hand interaction supported with agent-based training can help to improve productivity and interactiveness. Furthermore, the expert reviewers' feedback about the ml-agents for increasing learning efficiency was positive, which supported the hypothesis behind the implementation of the machine learning agents. To get input from the subject experts, two STEM teachers with experience in secondary school are engaged to expert advice on the learning flow and adopted approach. Finally, the realism approach received optimistic feedback from reviewers by providing real-time hand interaction with learning material.

Due to resource constraints, the teacher may not be able to be present to conduct these chemical reactions with the student; such AR solutions can help to overcome the learning barriers. Thus, using agent-oriented approach with hand interaction technology, AR can offer new possibilities in innovative learning, where the provision of the actual objects is not possible due to cost or availability. Kinesthetic learning in AR by interaction techniques is a new field of research. It offers a new form of remote learning whose development is essential to reinforce learning goals. However, the detailed evaluation of the system, comparing students' knowledge gain and the effectiveness of the hypothesis, needs more structured control group experiments. Hence future work will include the control group experiments with the students to compare with traditional learning.

Ethics approval

Appropriate procedure adopted.

Consent to participate

Appropriate procedure adopted.

Consent for publication

Appropriate procedure adopted.

Authors' contribution

This paper is part of PhD work of primary author. Design, development, evaluations and draft writing are done by primary author. Second author has supervised this research and the findings and contributed to final draft of paper.

Declaration of Competing Interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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