Virtual Humans for Temperature Visualization in a Tangible Augmented Reality Educational Game

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Abstract

Our primary objective is to enable effective game based learning approaches in tangible augmented reality. In game based learning there is often a tradeoff in motivation between the educational aspects and game aspects. For example, consider our previous work - a tangible augmented reality application for passive solar energy education (AR-SEE), in which users learn about the science behind architectural design by interacting with a tangible model house and an augmented reality-based visualization of energy transfer within the house. This research extends AR-SEE to begin to convert this educational simulation into an effective educational game by introducing gaming elements, such as interactive virtual humans. Although it is known that AR-SEE does enable learning, it is unknown how the addition of interactive virtual humans will affect user perception of temperature data and learning.

In this paper, the goal was to compare user perception of two approaches to temperature data visualization in in tangible augmented reality on mobile phones: 1) the current particle-based visualization (i.e., based on the science of energy transfer) and 2) novel virtual human-based visualizations. The game was intended for high school students. However, as a preliminary study, we conducted a user study with 27 3rd and 4th year architecture students that compared these two visualization approaches and their impact on temperature estimation, motivation, and perceived learning effectiveness. In the future, we plan to integrate this game into high school curricula.

Keywords: Augmented reality, education, visualization.

Index Terms: H.5.1 [Information Interfaces and Presentation]: Multimedia Information Systems—Artificial, augmented and virtual realities;

1 Introduction

In Tangible Augmented Reality (AR), the combination of physical interaction with overlaid virtual information can benefit hands-on learning [10–12] and can enable effective educational simulations. By converting these educational simulations into educational games, user motivation can potentially increase, which will likely have a positive benefit on learning outcomes. This work looks at converting an existing tangible AR educational simulation Augmented Reality for Passive Solar Energy Education (AR-SEE) into an educational game. In this paper, we integrate virtual humans as an additional visualization modality and investigate how this impacts user motivation for learning and perception of the underlying simulation data.

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The goal of our existing educational simulation, AR-SEE, is to educate users about the science behind architectural design and how this impacts temperature and energy usage in the home. Users can physically change the architectural features (i.e., window placement, roof choice) of a tangible model house, which affects the AR visualization. Energy transferred from the sun into the house is visualized through a particle simulation of Brownian motion. That is, the atoms in air move more vigorously when it is a higher temperature than when it is a lower temperature. Beyond this, we aimed to integrate virtual humans, who would also visibly react to the temperature changes, as part of a game.

We extended AR-SEE to include virtual human inhabitants that perform animations based on the temperature data the same data that the particle visualization is based upon (figure 1). We conducted a within-subjects user study with 27 3rd and 4th year architecture students (i.e., potential end users of the application) and investigated how particle-based visualization and virtual human-based visualization may impact temperature perception and motivation in a tangible augmented reality environment on a mobile phone.

2 Background Literature

2.1 Game-based Learning

The primary impact of game based learning is on the motivation to learn [4, 13, 14]. One of the most difficult challenges in game based learning is the integration of gaming elements and learning objectives, since in terms of user perception, usually one aspect overshadows the other and this can have a significant impact on motivation. Therefore, it is important to understand how the users perceive the different aspects of a game and how this affects motivation. For example, one aspect of many games that is of particular interest to us is interactive virtual humans. This paper investigates how users perceive and interact with virtual humans as a data visualization approach in tangible augmented reality gaming environments.

2.2 AR in Education

AR is well suited to address a need in STEM education: contextualizing abstract concepts [2]. In STEM Education, AR-related research primarily focuses on usability rather than formal evaluation of learning. This is linked to technological limitations, in particular difficulties related to the scalability of manipulatives due to the standard optical tracking approach [8]. Almost all prior research on AR in STEM education has employed standard optical tracking (i.e., image-based, video-see-through) of paper-based fiducial markers to enable physical manipulatives [1,5,6].

2.3 Virtual Humans in Education

Virtual humans have been very effective in education as instructors and communication skills trainers [9]. Ieronutti and Chittaro used virtual humans as a coach/Instructor in an educational virtual environment. The virtual humans explained physical and procedural tasks, allowing learners to receive more practical explanations which are easier to understand. The virtual humans could communicate with students in a natural way by exploiting verbal and non-verbal communications [7].

Figure 1: Top: User interaction with tangible AR, Middle: Virtual Human visualization of temperature, Bottom, Particle visualization of temperature

2.4 AR-SEE: Augmented Reality for Passive Solar Energy Education

This research is based on the AR-SEE project which is an Augmented Reality application for mobile phones for Passive Solar Energy Education. AR-SEE combines a mobile phone-based AR with a physical model of a house. Users interactively change the parameters of the house (e.g., roof style, windows, building materials), which changes the internal temperature inside the house. These changes are visualized through a particle visualization of energy transfer shown in situ on the phone. The application was designed to provide students the scientific knowledge about how passive solar energy affects the temperature inside the house, which affects energy usage efficiency [3].

2.4.1 Interaction

A user has three complementary ways to interact with AR-SEE (figure 1). Users look through the phone and point it at the big green marker. They can freely walk around and view the simulation. They can physically zoom in to see what is happening inside the house.

The second way of interaction consists of the phones touch screen interface that includes three buttons located on the right side of the screen and which allow the user to select the material for the roof of the house, the material for the base of the house, and the x-ray button which makes the house partially transparent to allow the user to see either the visualization (e.g., particles or the virtual humans) inside the house.

Users are able to modify the architecture of the house through the tangible interface (figure 2), which consists of small markers to select between two different types of roofs and select from four different types of windows. When the users desire to change the roof or window, they hold the phone with one of their hands, remove one of the small markers and put in another marker with the other hand. As a result, the virtual house will change its architecture according to the marker that is chosen.

2.4.2 Visualization

The particle visualization (figure 1 bottom) visualizes the Brownian motion effect by using little yellow cubes distributed around the living room in the house. These cubes move around the space of the room with a speed directly proportional to the temperature inside the house. For example, if the temperature is at its highest the particles move faster and when the temperature is at its lowest the particles move slower. This type of visualization has the objective to approximate the behavior of the particles in the air and provides the user with a conceptually scientific approach to show how the design of the house affects its temperature.

2.4.3 Motivation for Using AR in AR-SEE

The primary reason we aimed to use AR in this kind of learning experience is because it can potentially offer educational benefits that a desktop simulation cannot offer. Specifically, we hypothesize that AR has two major educational advantages 1) physical manipulatives and 2) in situ visualization. There has been much research that has shown the advantages of physical manipulatives in education and this has been supported in previous educational AR research as well [1, 5, 6]. Also suggested in the AR education literature is that AR has the capability to make the invisible processes in the physical world visible.

3 Virtual Human Visualization in AR-SEE

In this paper we extended AR-SEE to include animated virtual humans as visualization for temperature data. There are three virtual humans living in the home. They all perform the same animations at the same time, except for one that sits while others are chatting. Five animation states (figure 2) were created for the virtual humans that mapped to temperature level sitting/chatting (less than 81 degrees Fahrenheit), fanning self (81 to 85 degrees), wiping brow (86 to 90 degrees), dizzy (91 to 95 degrees) and falling forward (above 95 degrees). All of the animations, besides fanning self and wiping brow were purchased from mixamo.com; wiping brow was motion captured using a Microsoft Kinect and iPi Softs iPi recorder; fanning self was created manually in 3ds Max 2012.

Each unique animation maps to a specific level of discomfort with sitting and chatting being considered equal. Sitting/chatting where the lowest level of discomfort, followed by fanning self, wiping brow, dizzy and finally, falling forward which was considered the highest level of discomfort. These animations correspond to the same temperature ranges as the particle visualization (section 2.4).

3.1 System Description

The system used in the study consists of the following hardware and software components: 1) Phone: HTC Desire HD (4.3 inch screen, 1Ghz Processor, 768MB RAM, using 1024x768 camera resolution) with Android 2.1, 2) AR: Qualcomm QCAR SDK 1.0 +

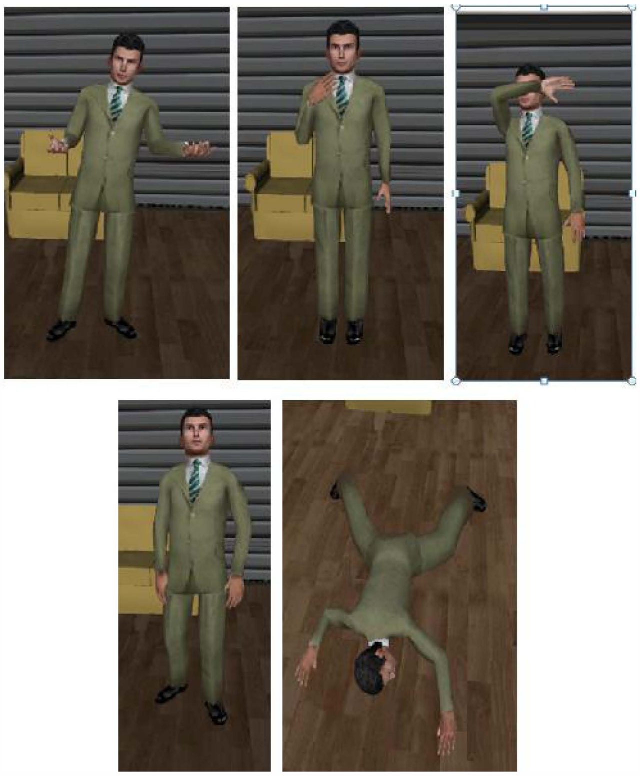

Figure 2: The animations for one of the virtual humans: chatting, fanning self, wiping brow, dizzy, fallen forward (i.e., fainted). The animations are mapped to increasing temperatures.

Unity 3.3.The system runs at approximately 20 frames per second (fps).

4 User Study

The objective of this within-subjects study was to investigate two different visualization techniques for temperature data and understand how they affect user perception of temperature in a mobile phone tangible augmented reality-based application. Participants progressed through two conditions in random order in which temperature changes were visualized with either: 1) animated virtual humans and 2) particle animation resembling Brownian motion (i.e., how atoms move in different temperatures). To perform the study tasks, all participants interacted with a tangible augmented reality interface on a mobile phone (section 2.5).

4.1 Hypotheses

In general we expected that participants would estimate a wider range of temperature changes because the virtual human animations at different temperatures are very different, whereas, the particles just change in vibration magnitude based on the temperature. Moreover, we expected that participants would be sympathetic to the virtual humans, which would increase the range of temperature estimation and also increase their motivation to learn with the virtual humans.

H1: Users will estimate a wider range of temperature changes when the changes are visualized with animated virtual humans instead of animated particles, leading to greater error in estimation with virtual humans.

H2: Users will perceive that the particles will be more helpful in estimating temperature.

H3: Temperature estimation will take longer with virtual humans than with particles, since the animations take time to play, whereas the particles instantly change vibration when the temperature changes.

H4: There will be no difference in configuration test errors between conditions when users try to find the best and worst configurations.

H5: Users will be more motivated to learn about passive solar energy with virtual humans-based visualizations than with particle-based visualizations.

4.2 Conditions

All participants interacted with both the virtual human visualization (described in section 3) (VIRTUAL HUMAN) and the particle visualization (described in section 2.4.2) (PARTICLE) in random order. There are a few differences between the study application and the AR-SEE application to better control the study. These differences are explained here.

Firstly, we wanted to neutralize the effects of prior knowledge in all conditions. Thus, for this study we randomized the effects of changing house parameters on temperature data before the study began, so that participants could not use prior knowledge of passive solar energy or their intuition about passive solar energy. Specifically, there were 2 different temperature data / house design configurations. All participants experienced both configurations, but with different visualizations. For example, if a participant began with Virtual Human visualization and temperature configuration B, then they would interact with particles visualization and temperature configuration A, and vice versa. Prior to beginning each condition, participants were reminded of the temperature/configuration randomization.

4.2.1 VIRTUAL HUMANS Condition

The virtual humans performed the same as was described in section 3. Prior to beginning this condition, participants were informed how the humans would react to relative temperature changes, but not the exact ranges. There were no other indications of temperature besides the animations.

4.2.2 PARTICLE Condition

Similar to VIRTUAL HUMANS, to visualize temperature, five different temperature ranges were used, which corresponded to five different movement speeds for the particles. In the first level of speed (the lowest, i.e., particles move the slowest possible) the temperature is in a range of less than or equal to 80 degrees Fahrenheit. In the following second, a third and fourth level, the temperatures ranges between 81 and 85, 86 and 90 and 91 and 95, respectively. The last level is where one can observe the particles move at their highest speed; this happens when the temperature reaches values more than 95 degrees Fahrenheit. Note that, the particle simulation, while conceptually accurate, is not scientifically accurate with respect to how fast the particles move. Prior to beginning this condition, participants were informed that temperature would affect the speeds, but not the exact ranges. There were no other indications of temperature besides the particle visualization.

4.3 Environment and Population

The study was conducted in a quiet, air conditioned laboratory environment. The population consisted of 27 3rd and 4th year undergraduate architecture students 20 to 30 years. The participants had none or very little knowledge of AR. Most had moderate knowledge of Passive Solar Energy strategies in architectural design, which is why we randomized the temperature values and told participants not to rely on their previous knowledge. Participants had none or very little knowledge of Brownian motion.

4.4 Procedure

The study procedure consisted of the following steps:

1. Pre-interview - established participants' prior knowledge of PSE through a self-rated Likert scale. Demographic information (e.g., age) was also collected.

2. Interface training - trained participants on how to interact with the user interface and demonstrated all the functionality of the simulation. The visualization was not displayed during this training.

Phases 3 and 4 were each performed twice, once for each condition:

3. Directed Interaction: PARTICLES/VIRTUAL HUMANS conditions - Participants were given verbal instructions to complete a series of simple one step tasks using the touch screen and tangible interfaces. They were told to consider that the initial temperature inside the house was 85F. A single instruction was given and then participants performed the task. After each instruction that modified the configuration of the house, they had to estimate the new temperature value according to the visualization changes they saw inside the house. There were 9 instructions in all. The instructions were the same in both conditions.

4. Optimization phase PARTICLES/VIRTUAL HUMANS condition - During this phase, participants used the same interface from phase three with the particles visualization and were given the task of initially finding the optimal house configuration that makes the temperature inside the house the lowest possible. After that, they had to configure the worst case scenario in which the temperature would reach its highest. Again, they had to find both configurations by checking the visualization inside the house with no other information that could help to complete the task.

5. Post-interview - For the interview, the participants were asked to give their opinions on the software. This included a comparison between the two visualization options by using a self-rated Likert scale and explanation to describe the differences.

5 METRICS

We employed numerous metrics to assess temperature estimation, time and errors, passive solar energy knowledge, and motivation.

5.1 Temperature Estimation

Directed Interaction Temperature Estimation Error (DITEE) During the two directed instruction tests in phases three and four, after each instruction i was given, the user estimated the temperature Ev(i). At this point, there was a correct temperature value Cv(i) which was directly related to the visualization displayed in the phones screen (particles movement speed or virtual human behavior). The correct temperature value was not shown on the screen. The user knew that the first temperature for the initial house configuration was 85F. The estimated value Ev(i) was compared with the previous estimation Ev(i - 1). The difference between these two estimations is called estimated temperature variation ETV(i).

$$ETV(i) = Ev(i) - Ev(i-1) \tag{1}$$

To each estimated value, there exists a correct temperature value related to the visualization, then, the correct temperature variation CTV(i) is the difference between the current correct temperature Cv(i) and the previous correct temperature Cv(i-1).

$$CTV(i) = Cv(i) - Cv(i1) \tag{2}$$

After user completes each instruction i, there exist two values: the estimated temperature variation ETV(i) and the correct temperature variation ETV(i). The Estimation error per instruction EE(i) is the difference of these two last numbers.

$$EE(i) = ETV(i) - CTV(i) \tag{3}$$

Since the user made nine estimations corresponding to each instruction completed, there are nine Estimation errors. Finally, the

Table 1: Directed Instruction Temperature Estimation Error (Mean Fahrenheit degrees)

Condition	Mean	Std. Dev.	Std. Error
PARTICLES	5.06	2.61	0.52
VIRTUAL HUMAN	3.52	1.46	0.29

Directed Interaction Temperature Estimation Error (DITEE) was the average of the nine Estimation errors.

$$DITEE = \frac{\sum_{i=1}^{9} EE(i)}{9} \tag{4}$$

The idea of calculating the error considering the previous estimation is based on the fact that each estimation would be influenced by the previous estimation. Therefore, we used the relative change in temperature (ETV - CTV) to calculate the error instead of the raw temperature difference (Ev - Cv).

Virtual Human and Particles Effectiveness for Temperature Estimation - Additionally, they were also asked to rate the level of effectiveness of both visualization conditions to estimate the temperature in the house. We used a Likert scale of 1 to 5, 1 being minimally effective, and 5 being very effective.

5.2 Time

Directed Interaction Time - participants were given a series of short instructions (e.g., change the roof to a wide configuration). The total amount of time that it took participants to complete the task was logged.

Time for Best Configuration Test and Worst Configuration Test - The amount of time to find the best and worst configurations were recorded. In total, four times were logged: two for particles visualization and two for the virtual human visualization.

5.3 Configuration Test Errors

Best Configuration Test and Worst Configuration Test Errors - the correct configurations were determined before-hand. Each one of the configuration options that the participants failed to select correctly counted as an error. Turing each test, errors were logged.

5.4 Motivation

Virtual Human and Particles Impact on Motivation - participants were asked two questions (i.e., one for PARTICLES and one for VIRTUAL HUMANS) to rate their level of motivation to continue learning about how the house design impacted the temperature in the house with the virtual human and particle visualizations. We used a Likert scale of 1 to 5, 1 being minimal motivation, 5 being high motivation.

6 RESULTS AND DISCUSSION

Based on the results of a Shapiro-Wilk test, the data appeared to be normal and thus we used parametric tests for analysis. Note that in some cases a few participants had some missing data and thus the degrees of freedom for those cases are lower (e.g. 24).

6.1 Temperature Estimation

The descriptive statistics of the Directed Instruction Temperature Estimation Error for both PARTICLES and VIRTUAL HUMAN visualizations are shown in Table 1. Using a paired t test, we found a significant difference between the conditions ($t(24) = 3.112$, $p<.05$). The means suggest that participants were more accurate at estimating temperature with virtual humans. Thus, H1 is rejected. 5-Likert Temperature Estimation Effectiveness: There was no significant difference between the Effectiveness of the virtual human condition in helping to estimate the temperature inside the house (mean 3.96) and Effectiveness of the particles condition in helping to estimate the

Table 2: Virtual Human and Particles Effectiveness (Mean Likert scale 1-5)

Condition	Mean	Std. Dev.
PARTICLES	3.65	1.05
VIRTUAL HUMAN	3.96	1.03

Table 3: Directed Instruction Time (Seconds)

Condition	Mean	Std. Dev.	Std. Error
PARTICLES	254.68	55.33	10.64
VIRTUAL HUMAN	227.76	55.81	10.74

Table 5: Worst Configuration Test Time (Seconds)

Condition	Mean	Std. Dev.	Std. Error
PARTICLES	62.68	39.14	7.53
VIRTUAL HUMAN	67.48	59.09	11.37

Table 6: Best Configuration Test Error (Fahrenheit degrees)

Condition	Mean	Std. Dev.	Std. Error
PARTICLES	1.76	3.79	0.74
VIRTUAL HUMAN	1.84	3.89	0.78

temperature inside the house (mean 3.65). A Wilcoxon Signed-rank test shows that there is no a significant effect of Condition ($Z = 0.995$, $p=0.32$, $r = 0.137$) (Table 2). Thus, H2 cannot be accepted.

6.2 Time

Table 3 shows the mean times to complete the .Directed Instruction in both conditions. Using a paired t test, we found a significant difference between PARTICLES and VIRTUAL HUMAN ($t(26) = 2.172$, $p<.05$) with Directed Instruction Time. The means suggest that users spent less time with virtual humans.

Tables 4 and 5 give the mean times for the two conditions when the optimization test was done. The table includes the mean times for finding the best configuration and the worst configuration. We found no significant differences in Configuration Times in both best and worst configurations between PARTICLES and VIRTUAL HUMAN ($t(26) = 0.021$, $p=.98$ and $t(26) = -.427$, $p=0.67$).). Thus, H3 cannot be accepted.

6.3 Configuration Test Error

The means of the Best and Worst Configuration Errors are given in Tables 6 and 7. We found no significant differences in either best or worst configurations between PARTICLES and VIRTUAL HUMAN ($t(25) = -.068$, $p=.94$ and $t(25) = 0.428$, $p=0.67$). Thus, H4 cannot be rejected. In general, errors were very low in both conditions. From this we can conclude that both methods were effective in visualizing relative temperature change.

6.4 Motivation

There was a significant difference between the Motivation to learn about the effect of the house design on temperature when using the virtual humans (mean 4.5) and Motivation to learn about the effect of the house design on temperature when using the particles visualization (mean 3.8). (Table 8) Thus, H5 cannot be rejected.

A Wilcoxon Signed-rank test shows that there is a significant effect of Condition ($Z = -2.65$, $p < 0.05$, $r = 0.36$). This result was supported by the post-study interview in which most of the participants expressed preference by the human visualization because it is considered more realistic than particles. In addition, during the interaction the users showed sympathy with the reactions of the virtual humans by smiling, laughing or showing expressions of having fun.

6.5 Discussion

Temperature Estimation: Surprisingly, results showed that users estimations of the temperature were significantly more accurate with the virtual humans. These results may be due to the fact that the participants can relate human reactions to the temperatures inside the house based on their personal previous experiences or feelings. On the other hand, they were less precise in the condition of the particles because it was more difficult for them to differentiate the speed of the particles movement. Other reasons for these differences may be the differing degrees of freedom in each visualization. More work is needed in the future to investigate this.

The evaluation of the estimation effectiveness results did not show conclusive results. That is, it is unclear why people would prefer PARTICLES or VIRTUAL HUMANS. Although, comments like "I like to see the human, but particles are more distinctive", or "People's reaction are more interesting but since particles occupied more space, I could estimate the temperature easier" were provided for people that thought particles were more effective. Contrarily, students who support the major effectiveness of Virtual Human gave comments like "Comparing attitudes makes it easier to compare temperatures", "Humans are easy to read" and "It is clear how their feelings were".

Time: The virtual humans condition showed shorter times to complete the directed instruction. This could be due to that when the users changed something in the particles condition; it took them more time to notice what was happening inside the house because they had to move closer to the scenario in order to see the differences in the speed of the particles movement. This may be due to the fact that the particles seemed less familiar to the participants. There were likely no significant differences in the configuration tests time since participants had become familiar with the particles. In contrast, this highlights one advantage of the virtual humans in that, users very quickly understood what the virtual humans were trying to convey in their animations due to their familiarity with human reactions to heat.

Motivation: As expected, the virtual human visualization had a major impact on users in their motivation to learn more about PSE. The quantitative data was backed by the qualitative post-interview in which many participants expressed their preference for this condition. The participants expressed ideas like: "People are easier to understand because I know what the people feel cause we feel in the same way" and "It is funny to see the reactions of people".

6.5.1 Study Limitations

The main limitation of the study is the differences between the visualization approaches. If we had changed the color of the particles, for example, results may have differed. In the future we plan to conduct studies with additional conditions to make the visualizations more directly comparable.

Table 4: Best Configuration Test Time (Seconds)

Condition	Mean	Std. Dev.	Std. Error
PARTICLES	114.83	48.25	9.28
VIRTUAL HUMAN	114.57	58.90	11.33

Table 7: Worst Configuration Test Error (Fahrenheit degrees)

Condition	Mean	Std. Dev.	Std. Error
PARTICLES	1.42	3.54	0.69
VIRTUAL HUMAN	1.07	2.59	0.50

Table 8: Virtual Human and Particles Impact on Motivation (Mean Rank Likert scale 1-5)

Condition	Mean	Std. Dev.
PARTICLES	3.8	1.09
VIRTUAL HUMAN	4.3	0.70

7 Conclusion

As we expected, virtual human visualization of temperature data enabled higher motivation than the particle visualization for learning in the tangible AR environment. However, we were surprised that the virtual human visualization enabled significantly lower temperature estimation error than the particle visualization. This was the perception of users as they interacted with tangible interfaces and visualized the results on a small hand-held screen of the mobile phone. Thus, there is an inconsistency in user perception, which may have an impact on learning outcomes. We expect that these visualizations can be fine-tuned (e.g., make the particle movement more subtle or make the virtual human animations more dramatic) to elicit more consistent perception of temperature.

The main takeaway message of this paper is that perception in AR can influence motivation and potentially learning. Thus, one must take care in designing visualizations and take into account the emotional effect it may have on learners. Because this study was on students in 20s-30s, it is still unclear how these visualizations will affect children. However, because this preliminary study was a human perception study, we expect that there would be some correlation to perception in high school children. More research is needed in the future to confirm this.

In the future we plan to further investigate the effects of these virtual human and their combination on learning outcomes, and look at how this may impact learning and interaction in more complex tangible AR educational game environments, specifically in the high school student population.

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