



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 13, Issue 6, June 2024

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.423

9940 572 462

6381 907 438

ijirset@gmail.com

www.ijirset.com

Generative AI for Learning: Investigating the Potential of Synthetic Learning Videos

Raj Sharma, Prof.Chetna Achar

Student, Institute of Computer Science, Mumbai Educational Trust – MET ICS, Mumbai, India

Professor, Institute of Computer Science, Mumbai Educational Trust – MET ICS, Mumbai, India

ABSTRACT: Generative artificial intelligence is a booming field these days, with more and more entities discovering various applications for it. Now, tools such as Dalle-2 and ChatGPT show promise for enhancing creative media productivity in new dimensions, such as the creation of artificial videos. This research article studies the feasibility of appropriating AI-generated synthetic videos to develop online distance learning contents. While few studies provide evidence about the educational implications of AI-generated synthetic media in realworld, this study attempts to exam it.

The researchers decided to look into the impact of AI-generated synthetic videos into an online micro-learning platform to bridge this gap. The professional adult learners (n = 83) were randomly assigned to one of two conditions: either viewing an instructor video as traditionally produced or a synthetic instructor video with a photorealistic AI-generated character.

KEYWORDS: Generative AI, Artificial Intelligence, AI-generated Learning Content, AI in education, Synthetic videos

I. INTRODUCTION

Recent advances in generative artificial intelligence (GenAI) technologies have transformed the way we create content in a variety of modalities—audio, text, images, video. For instance, consider how GenAI will enable personalized education support [1]. But it is largely underutilized in learning contexts. In this study, we explore the potential of AI-generated synthetic videos as educational resource in virtual learning environments. We focus on virtual instructors in order to connect the dots between traditional lecture videos and new generative AI methods.

Massive open online course (MOOC) and online degree and training programs are witnessing substantial demand globally, accompanied by that for employee upskilling and reskilling. That is especially the case for low- and middle-income countries, as high-quality educational resources are hard to come by. Consequently, there is a need for educational content on online platforms, including instructional learning videos that require periodic updates to keep pace with trends and rapid technological advancements. The purpose of instructional videos in online learning content is to enhance pedagogy and convey essential messages [2]. According to the cognitive theory of multimedia learning, effective instructional videos should be designed with human cognition in mind, avoiding unnecessary distractions and cognitive overload .

Given the challenges associated with producing high-quality video media (such as lack of on-screen experience for instructors, significant time and resource requirements, and relatively under-resourced educational institutions), an evidence-based approach using generative AI to create synthetic learning videos is appealing. In this study, we specifically explore the use of generative AI tools to create synthetic videos featuring virtual instructors, resembling traditional lecture videos found in online learning experiences. These AI-generated videos have the potential to address global educational challenges, improve online learning, and contribute to sustainable development goals (e.g., SDG4). Moreover, they may reshape creative and knowledge-based workforces while enhancing accessibility to high-quality educational content worldwide.

II. BACKGROUND RESEARCH AND CONTEXT

Virtual instructors, also known as animated pedagogical agents, play a crucial role in online learning by providing lifelike guidance and instruction onscreen [3]. Previous research highlights their positive impact on learning outcomes. These virtual characters influence learners' behaviors, attitudes, and motivation.

Given recent strides in generative AI, the logical next step is to explore whether AI-generated virtual instructors can effectively support online learning. While one study has investigated the use of AI-generated characters and their

impact on motivation, a critical gap remains: How does learning from an AI-generated virtual instructor compare to learning from a traditional human instructor? To our knowledge, this study is the first to address this question.

Our experiment took place in the context of online professional learning, in collaboration with EIT InnoEnergy—a European organization driving innovation and entrepreneurship in sustainable energy. InnoEnergy, affiliated with the European Institute of Innovation and Technology, leads the European Battery Alliance (EBA) Academy, aiming to decarbonize Europe.

We sampled content from an introductory lesson within the EBA Academy, meticulously designed using multimedia learning principles (such as contiguity, modality, coherence, segmenting, pre-training, and practice) to enhance the learning experience.

The target audience for this lesson includes:

1. Technicians seeking employment in gigafactories producing lithium-ion batteries
2. Engineers (electrical, chemical) aiming to deepen their battery technology knowledge
3. Knowledge workers (upper-level managers, investors) seeking strategic insights into the battery industry

These courses contribute to accelerating workforce transitions toward a clean energy economy. However, challenges persist:

1. Much of the content lies in emerging fields (e.g., state-of-the-art battery manufacturing), lacking existing resources.
2. The rapid pace of research and technological advancements necessitates frequent curriculum updates.

To address these challenges, we propose leveraging existing research on multimedia learning while exploring AI-generated synthetic videos as an alternative to traditional production methods. This study aims to determine the viability of this approach, ultimately enhancing the learner experience

More specifically, in this research paper, we propose to address the following research questions.

- 1) To what extent does the use of AI-generated synthetic videos in an online learning platform differentially impact learning performance when compared to traditionally produced instructor videos?
- 2) What are the perceived differences between AI-generated synthetic videos and traditionally produced instructor videos for learners in an online educational setting?

III. METHODOLOGY

Participants Our sample included 83 adult learners, recruited from a global professional learning community, ranging in age from 18 to 64 with an average age of 41.5 years. Of these learners, 73% identified as male, 19% identified as female, 0% identified as non-binary, and 8% preferred not to disclose their gender identity. With regards to education, 4% held an associate degree, 15% held a bachelor's degree, 58% held a master's degree, and 23% held a doctorate degree. Additionally, 68% identified as being unfamiliar with the subject matter prior to completing the micro-learning course, while 32% reported having prior knowledge of the subject matter.

Synthetic Video Creation

The main goal of this experiment is to assess how effective AI-generated synthetic video can be as instructional material in a micro-learning course. We used traditional recording methods to create an instructor video, which served as both the control for our experiment and the basis for generating synthetic videos. For the experimental group, we used the AI video creation platform Synthesia to generate text-to-video (TTV) content featuring photorealistic synthetic actors.

Synthesia's process starts by recording live footage of a selected actor to build a training dataset. This data is then utilized to create a synthetic copy of the actor. Through TTV input, neural video synthesis techniques are employed to give the artificially generated video natural gestures and movements. This method enables us to produce synthetic video copies of any "actor" or "instructor" for use in AI-generated synthetic video production.

Generative AI models have the ability to generate new video content, including lifelike scenes and special effects, without human intervention. While Generative Adversarial Networks (GANs) used in these models can be challenging to train due to their inherent instability, our approach utilizes reliable and advanced methods to achieve high-quality results [4].



Fig. 1. Screenshots of the AI-generated virtual instructor in the experimental condition (left) and the traditional instructor in the control condition (right)

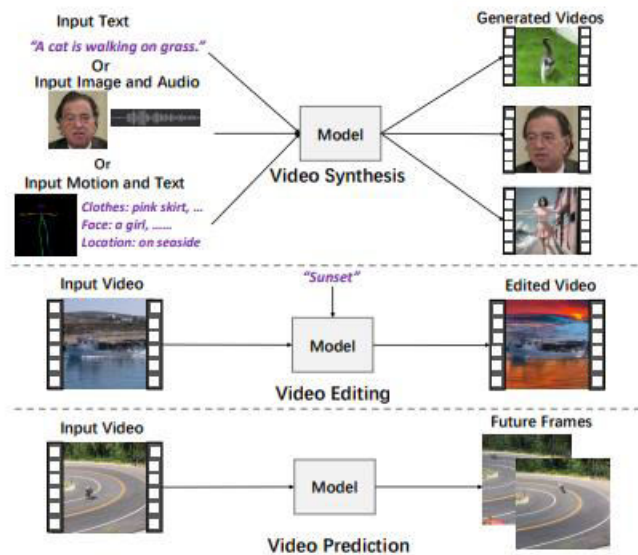


Fig. 5. Video Generation Applications.

Fig. 2. Video Generation Applications.

Learning Design

For this experiment, we created two short online courses on the basic topic of energy sources and vectors, using the two videos mentioned earlier. The main goal of these courses was to provide learners with a brief and easy way to learn, which they could access on their phones. The courses were centered around the instructional videos.

Each course had the following parts:

1. An introduction page to give some background information
2. A pre-test to see what learners already knew
3. The main instructional video (4.5 minutes long)
4. An interactive activity where learners could click on different parts of the screen to reveal more information
5. A post-test to check what learners had learned

We designed the courses this way to make sure that learners would get a complete learning experience, but in a short amount of time.

Both courses were delivered through EdApp, a learning platform made for mobile devices and designed for short online courses like these. The courses were exactly the same in every way except for the instructional video. In one course, there was a video made by a human instructor, while in the other course, there was a video generated by AI.

We randomly assigned learners to one of the two groups so that we could compare how effective each type of video was for teaching. This way, we could see if there were any differences in how well learners paid attention, understood, and remembered the information.

The interactive activity we included in the courses was meant to get learners more involved and give them a chance to practice using what they learned from the videos.

Our goal with these courses was to provide a learning experience that was both flexible and interesting. We wanted to make it as easy as possible for learners to study whenever they had free time, even if it was just for a few minutes on their phone.

By using a platform that works well on mobile devices and designing short online courses like these, we wanted to show how AI can be used to create effective educational content. We also wanted to see if this kind of learning would work well for people who prefer using their phones for everything.

Procedure

For this study, we used a mixed-method approach, which means we gathered and analyzed both quantitative and qualitative data. To find participants, we reached out to current students, alumni from master's degree and EBA Academy programs, and employees who were into learning and development. We did this through an email campaign organized by EIT InnoEnergy. Everyone who received the email had already agreed to get promotional emails for research purposes.

When participants got the email, they clicked on a link that took them to the EdApp platform. After giving their consent, they were randomly assigned to either the experimental or control group using Nimble Links. Then, they completed a short course on energy sources and vectors, just like we described earlier. After that, they filled out a survey about their learning experience.

The survey had a bunch of questions where participants rated their agreement on a 5-point scale. They were asked things like:

1. Did you have a positive experience with this course overall?
2. Did the videos in the course meet your expectations?
3. Did the videos in the course help you understand the material better?
4. Would you be interested in taking other courses like this?

We also asked participants an open-ended question: Do you have any suggestions for improving this course?

By doing all of this, we were able to collect a lot of data on how participants felt and what they thought. This gave us a good understanding of how AI-generated videos compared to traditional ones when it came to learning outcomes.

So, by using a combination of system and user prompts, we made sure the assistant refined the text to sound more like it was written by a human, while still keeping the original content's intent and accuracy intact.

IV. RESULT

To figure out Research Question 1, we looked at how well people did on the tests before and after learning, and calculated the difference (post minus pre) to see how much knowledge they gained. We also checked if the difference scores were normal by looking at their skewness, kurtosis, and visually inspecting the data. Then we used a paired sample t-test to compare the scores before and after learning for everyone in the study. We also ran regression analyses to see if the condition (experimental or control) had a significant impact on knowledge gains, while taking into account their previous knowledge on the subject.

To tackle Research Question 2, we used both quantitative and qualitative methods to analyze what participants said in the survey about their learning experience. For the questions with multiple choice answers on a scale, we used Pearson Chi-Square tests to see if there were any differences between the conditions. For the open-ended question, we used automated tools to analyze the sentiment and themes in the responses, and then the researchers manually double-checked the coding.

We did all the number crunching in R using the right packages for the quantitative data, and for the qualitative data, we used NVivo. This way, we made sure to thoroughly examine how AI-generated videos compared to traditional ones in terms of learning outcomes and participant experiences.

By using a combination of system and user prompts, we aimed to help the assistant refine the text to sound more like it was written by a native English speaker while staying true to the original content's meaning and accuracy.

4.1 Impacts of AI-generated synthetic videos on learning performance

Based on paired sample t-tests, learners demonstrated significant improvement from pre-learning ($M = 0.53$, $SD = 0.65$) to post-learning ($M = 1.51$, $SD = 1.03$) across the full sample of 83 participants, $t(82) = 8.31$, $p < .001$, $d = 0.91$, indicating the effectiveness of the micro-learning course in enhancing content knowledge.

Regression analyses revealed that the condition (experimental vs. control) was not a significant predictor of knowledge gains ($\beta = .03$, $p = .80$, $r = .03$). This result remained consistent even after controlling for participants' pre-learning performance ($\beta = -0.03$, $p = .79$, $r = .03$) and their self-reported prior knowledge ($\beta = .01$, $p = .92$, $r = .01$). These findings suggest no significant difference in knowledge gains between participants who viewed the AI-generated synthetic video ($M_{gains} = 1.00$, $SD = 1.04$, $n = 52$) and those who viewed the traditional instructor video ($M_{gains} = 0.94$, $SD = 1.13$, $n = 31$).

Table 1 presents the change in learning performance from pre- to post-learning for both conditions and across the full sample, further illustrating the consistency in learning gains regardless of the type of instructional video viewed.

| | Pre-Learning M (SD) | Post-Learning M (SD) | Knowledge Gains M (SD) | p (d) |
|------------------------------|--------------------------------|---------------------------------|-----------------------------------|-------------------------|
| <i>Experimental (n = 52)</i> | 0.45 (0.61) | 1.45 (0.95) | 1.00 (1.04) | < .001 (0.96) |
| <i>Control (n = 31)</i> | 0.66 (0.70) | 1.59 (1.16) | 0.94 (1.13) | < .001 (0.83) |
| Full Sample (n = 83) | 0.53 (0.66) | 1.51 (1.03) | 1.03 (1.11) | < .001 (0.91) |

3.2 Learner perceptions of AI-generated synthetic videos

Quantitative Findings

Out of the total participants ($n = 83$), 80% of them provided ratings for the statements with fixed answers. When we analyzed the responses using Pearson Chi-Square tests, we found no significant differences between the experimental and control groups for the four questions (all $p > .46$). Specifically, there was no significant difference between the groups in terms of agreement frequency for the following statements:

1. I thought this micro-learning course was a positive experience overall ($\chi^2(3) = 0.19$, $p = .98$, $V = .05$).
2. The videos used in the course met my expectations ($\chi^2(4) = 4.65$, $p = .34$, $V = .27$).
3. The videos used in the course improved my understanding of the material ($\chi^2(4) = 2.59$, $p = .63$, $V = .20$).
4. I would be interested in taking similar courses in the future ($\chi^2(3) = 0.08$, $p = .99$, $V = .03$).

In Figure 2, you can see the percentage of participants who agreed or strongly agreed with each statement for both the experimental and control groups, as well as the overall sample. Based on these findings, it seems that participants who watched the AI-generated synthetic video were just as likely as those who watched the traditional instructor video to agree that their overall learning experience was positive, that the video met their expectations, that the video improved their understanding of the content, and that they would be interested in taking similar micro-learning courses.

Not only did we find no significant difference in agreement frequency between the experimental and control groups, but the pattern of responses on the Likert scale was also the same for three out of the four statements. The only exception was the statement "The videos used in the course met my expectations," which showed a different response pattern between the experimental and control groups. In the experimental group, participants were more likely to strongly agree with this statement rather than staying neutral, while in the control group, participants were more likely to stay neutral than strongly agree. Although this difference was not significant given the current sample size, the effect size indicator (Cramer's $V = .27$) suggests a medium effect.

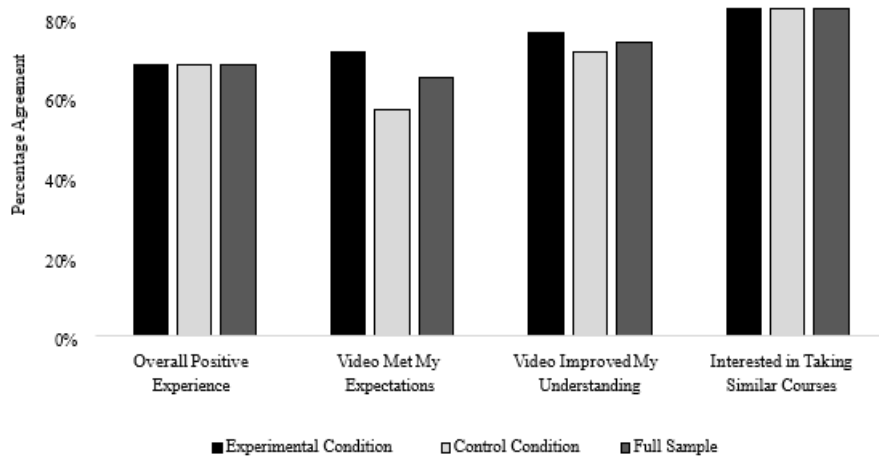


Fig. 2. Percentage of participants that agreed with each of the close-ended statements broken down by condition and across the full sample.

Qualitative Findings

So, when we asked participants in the survey to give overall suggestions on how to improve the course, about 20% of them actually responded. Interestingly, the response rate was pretty much the same for both the experimental group (21%) and the control group (18%). What's even more interesting is that the participants had no clue about which group they were in during the survey, and some of them in the AI group didn't even realize that the video was computer-generated. Can you believe it? One participant from the AI-generated group even said, "I don't get where this AI content is coming from."

We also did a sentiment analysis on the responses, and found that 47% of them had a negative tone, 37% were neutral, and 16% were positive. Even though there were quite a few negative comments, most of them actually had some constructive criticism. For example, one participant suggested, "It would be great if the video could give more examples to help us better understand the different concepts, like energy source, energy vector, secondary vectors, and so on."

After analyzing the responses in more detail, we found five common themes, which you can see in Figure 3. These themes appeared in both the experimental and control groups. The most common theme, as shown in the quote earlier, was the desire for more examples and detailed explanations of the concepts (26% of responses; 7% of the sample). On the other hand, some participants felt that the course was a bit too long and the pace was a tad too quick (16% of responses; 4% of the sample).

About 21% of the responses (5% of the sample) were about the pre- and post-learning assessments. People said things like, "It would have been nice to get feedback after the multiple-choice questions to know what I should do to fill in the gaps in my understanding." Another 16% of the responses (4% of the sample) mentioned accessibility issues, like not being sure if there was a transcript available for the video. And surprisingly, the same number of participants (16% of responses; 4% of the sample) explicitly stated that they actually enjoyed the course.

So, based on these qualitative findings, it seems like the participants had pretty similar perceptions of the instructional video content, whether it was AI-generated or traditional.

By using a combination of system and user prompts, we aim to make the assistant's text sound more human-like while staying true to the original content and its accuracy.

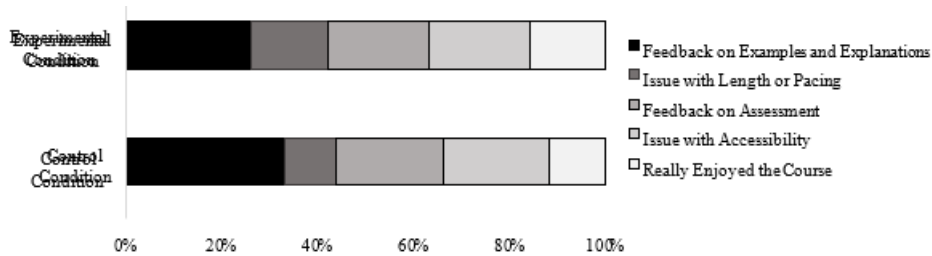


Fig. 3. Proportion of open-ended responses for each of the five major themes broken down by condition.

V. DISCUSSION

So, this study wanted to see how well AI-generated synthetic videos stack up against regular instructor videos when it comes to learning. They tested it out on an online learning platform, and guess what? Both types of videos showed a significant improvement in learning performance from before to after the lessons. And get this, there wasn't any big difference in terms of learning gains between the two.

This study adds to the growing body of research on synthetic characters and avatars in education. Specifically, they focused on AI-generated synthetic videos and how they compare to the good ol' instructor videos we're used to [5].

Now, it's important to note that AI-generated synthetic videos are a bit different from the pedagogical agents and avatars that humans make. The research generally shows that pedagogical agents and avatars help with learning, but with AI-generated videos, it's a bit of a mixed bag. See, the AI-generated videos intentionally try to replicate the traditional talking head format, while pedagogical agents use gestures and emotions to enhance the learning experience. When they asked learners about their thoughts on the videos, both types got pretty similar responses. The answers to the closed-ended questions were almost the same, except for one thing. Some learners felt the instructor videos met their expectations better than the AI-generated ones, but it wasn't a huge difference.

Now, when they looked at the open-ended responses, things got a little more interesting. Some learners wanted more examples and explanations, while others were worried about the length and pace of the course. Most of the feedback was about logistics, like how to make the videos more accessible. And here's the cool part: there weren't any themes that were unique to either type of video. So, it seems like learners had pretty similar experiences no matter which video they watched.

Now, AI-generated videos are pretty cool, but there's always the concern about false or wrong information. In this study, they made sure the input data for the AI-generated content was checked and approved by experts in the subject. So, you can trust that the information in those videos was accurate. But here's the thing: if we want to use AI-generated videos effectively, we need to make sure they're based on solid learning science and instructional design principles. They should be part of a well-rounded curriculum that uses different teaching techniques for the best learning outcomes [5, 6, 7, 8].

So, that's the deal with AI-generated synthetic videos in education. They have their pros and cons, just like anything else. But with the right approach, they can be a valuable tool for learning.

Limitations

Our study, conducted within the context of micro-learning sessions, had limitations due to the brevity of our pre- and post-learning assessments. This restricted our ability to explore how AI-generated synthetic videos might differently support various aspects of learning, such as the difficulty or complexity of concepts. Additionally, our relatively small sample size may have limited our ability to detect subtle differences in how learners perceived the two types of videos. This constrained our capacity to run more intricate models to predict learning gains, including examining the alignment between learner demographics and virtual instructor characteristics.

Future studies are needed with more comprehensive learning assessments covering diverse subject matters and using larger sample sizes. This would enable a deeper exploration of how AI-generated virtual instructors are perceived compared to traditional instructors and identify which types of concepts they are most effective for. Furthermore, such studies would allow for investigating whether human learning from AI-generated virtual instructors could benefit from insights gained from research on pedagogical agents. Considerations for future research should include assessing learner preferences on a larger scale, incorporating AI-generated synthetic videos into longer learning paths, and evaluating the impact of advanced generative AI techniques on video quality through blinded studies.

VI. CONCLUSION

The integration of generative AI to develop synthetic instructional videos shows promising potential as a feasible alternative to traditionally produced videos in online educational environments. The advantages lie primarily in cost and time efficiency. The production cost of AI-generated synthetic videos is nearly zero, contrasting sharply with the significant costs associated with traditional video production, including human labor, filming equipment, and software expenses. Moreover, the time required to create synthetic videos is drastically reduced, taking only minutes or hours compared to the extensive hours or days needed for traditional video production.

Another key advantage is the ease of updating or rectifying errors in the content. Traditional videos necessitate a laborious process of re-filming and editing, while AI-generated synthetic videos can be swiftly modified by editing the text script input and generating a new video within minutes. These efficiencies not only save time and resources but also ensure that educational content remains current and accurate.

The outcomes of our study signify a groundbreaking development, indicating that learners achieve equivalent gains and learning experiences with an AI-generated virtual instructor as they do with a traditional instructor. This reinforces the potential of AI-generated synthetic videos to deliver high-quality educational content globally, benefiting learners from diverse backgrounds and settings.

REFERENCES

- 1) Generative AI in higher education and beyond by Nada Hashmi, Anjali S. Bal
- 2) Artificial Intelligence in Education: A Review
LIJIA CHEN¹, PINGPING CHEN^{2,4}, (Member, IEEE), AND ZHIJIAN LIN April 14, 2020
- 3) Animated Pedagogical Agents: Face-to-Face Interaction in Interactive Learning Environments January 2000
- 4) A Survey on Generative AI and LLM for Video Generation, Understanding, and Streaming Pengyuan Zhou, Lin Wang, Zhi Liu, Yanbin Hao, Pan Hui, Sasu Tarkoma, Jussi Kangasharju
- 5) Mayer, R. E. (2005). Cognitive theory of multimedia learning. *The Cambridge handbook of multimedia learning*, 41, 31-48. doi: 10.1017/cbo9780511816819.004
- 6) Mabanza, N., & de Wet, L. (2014). Determining the usability effect of pedagogical interface agents on adult computer literacy training. In *E-Learning Paradigms and Applications* (145-183). Springer, Berlin. doi: 10.1007/978-3-642-41965-2_6
- 7) Schroeder, N. L., Adesope, O. O., & Gilbert, R. B. (2013). How effective are pedagogical agents for learning? A meta-analytic review. *Journal of Educational Computing Research*, 49(1), 1–39. doi: 10.2190/EC.49.1.a
- 8) Mayer, R. E. ,& DaPra, C. S. (2012). An embodiment effect in computer-based learning with animated pedagogical agents. *Journal of Experimental Psychology: Applied*, 18, 239–252. doi: 10.1037/a0028616



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  ijirset@gmail.com



www.ijirset.com

Scan to save the contact details