Problem-Based Learning and AI

586297-EPP-1-2017-1-EL-EPPKA2-CBHE-JP

Co-funded by the Erasmus+ Programme of the European Union

Document Info	
Project reference	586297-EPP-1-2017-1-EL-EPPKA2-CBHE-JP
Deliverable	D2.1
Dissemination level	Public
Date	13.04.2021
Document version	1.0
Status	Final
Authors	Ioannis Doumanis Gavin Sim Janet Read
Reviewers	Hariklia Tsalapatas Olivier Heidmann
Contributors	University of Central Lancashire
Approved by	Steering Committee

Co-funded by the Erasmus+ Programme of the European Union

Contents

586297-EPP-1-2017-1-EL-EPPKA2-CBHE-JP

1. Introduction

Problem-based learning (PBL) is an approach where students learn while actively engaging with meaningful problems (Kek and Huijser 2011). PBL helps students develop skills in solving problems and improved knowledge through collaborative and self-directed learning under an instructor's guidance. Below, we discuss how virtual agents can be used to support collaborative learning activities. A virtual Agents is a conversational AI programme (embodied and not embodied) designed to support student learning. The report covers the following learning environments: (1) online, (2) physical classroom, (3) VR and AR, (4) Mixed Reality (MR). As one-on-one tutoring is an important aspect of PBL (e.g., when the instructor provides individual student support), we also discuss personalised tutoring. Finally, we present some ideas on how to evaluate learning in these experiences using biometric research methods.

Section 2 provides a brief history of AI. Section 3 gives an overview of the learning environments that virtual agents can enable. Section 4 discusses how virtual agents can be evaluated using biometric methods of research. Finally, section 4 summarises and concludes the community document.

2. History of Artificial Intelligence (AI)

Artificial intelligence first emerged within computer science in 1950s. John McCarthy, who coined the term "artificial intelligence" in 1955, stated, "As suggested by the term **'artificial intelligence'** we weren't considering human behaviour except as a clue to possible effective ways of doing tasks. The only participants who studied human behaviour were Newell and Simon. The goal was to get away from studying human behaviour and consider the computer as a **tool for solving certain classes of problems.**

586297-EPP-1-2017-1-EL-EPPKA2-CBHE-JP

Co-funded by the Erasmus+ Programme of the European Union

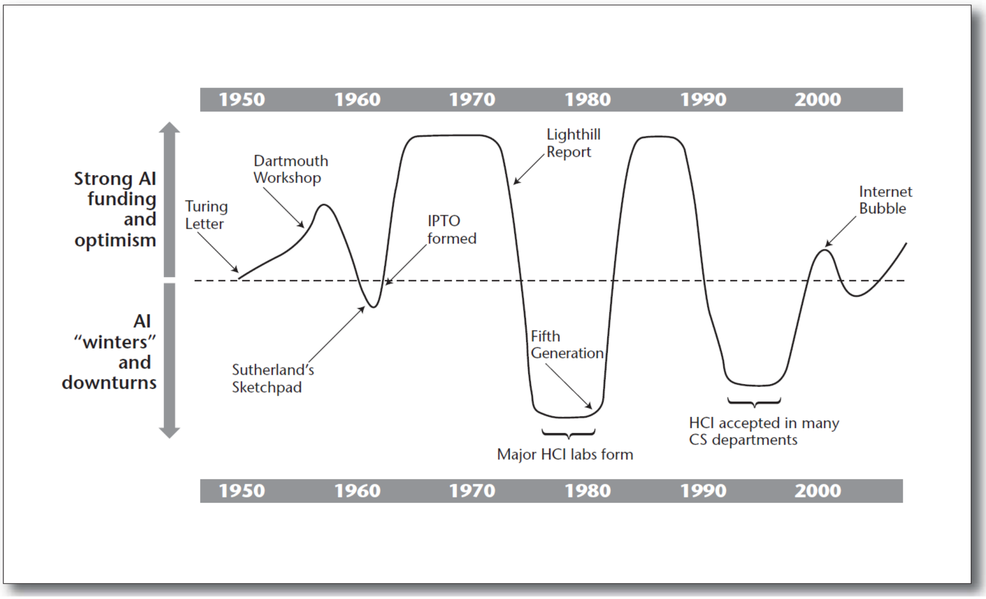

Figure 1: History of AI.

Thus, AI was created as a branch of computer science and not as a branch of psychology." Within 1950s, there was a perception from pioneers of AI who viewed computers as locomotives of thought, which might **outperform humans in higher mental work** as prodigiously as they outperformed them in arithmetic.

Over the subsequent decades, masses of funding was given to AI, and with a view by Nobel laureate and AI pioneer Herb Simon wrote in 1960, *"Machines will be capable, within twenty years, of doing any work that a man can do."* Figure 1 shows the findings of AI compared to other areas of computer science, notably HCI within the USA. Although this view has never materialised, advances in AI have continued, and the application of AI has moved away from a military context to a more social and practical stance in areas such as education. Within 1960s there was concern over the advancement of AI systems and when they would advance and surpass human intelligence. I. J. Good stated that *"the survival of man depends on the early construction of the ultra-intelligent machine"* that *"could design even better machines; there would then unquestionably be an 'intelligence explosion,' and the intelligence of man would be left far behind."* There have been cases recently where Facebook shut down their robots after they invented their language and the developers were concerned with the dialogue Facebook shuts down robots after they invented their own language (telegraph.co.uk)

Co-funded by the Erasmus+ Programme of the European Union

Many of today's applications around the home, such as Siri and Alexa, rely on speech recognition. This area came to prevalence in the 1970s Nicholas Negroponte of MIT argued compellingly that for machines to understand the context in which they operate, they must be able to understand speech. Over the years, algorithms and speech recognition have improved, but perceptions of robots' capabilities from the 1970s have not materialised. In the 1970s Life magazine stated, "In from **three to eight years,** we will have a machine with the general intelligence of an average human being. I mean a machine that will be able to read Shakespeare, grease a car, play office politics, tell a joke, have a fight. At that point, the machine will begin to educate itself with fantastic speed. In a few months, it will be at genius level and a few months after that, its powers will be incalculable." We will not be able to reach these capabilities today.

3. Virtual Agents and collaborative learning

3.1 Online collaborative learning

In most online classes, collaborative learning occurs **asynchronously** (not in real-time when the actual conversation takes place) using multimedia (e.g., audio, video and animation) as a central means of interaction. Several multimedia platforms can facilitate this type of interaction. One of those platforms is VoiceThread[1] (see Figure 2). VoiceThread is an interactive communication tool that allows voice, video, and text commenting. Users can share multimedia files (i.e. images, videos, PowerPoint presentations, PDFs) and invite others to comment using one of the available modalities (e.g., video or text). The other platform is Padlet. Padlet is an online virtual "bulletin" board where students and teachers can collaborate, reflect, and share links and pictures in a secure location. The platform is cheaper than VoiceThread, and the UI is more streamlined. However, Padlet does not offer the ability to annotate a slideshow with multimedia information.

[1] https://voicethread.com/

Co-funded by the Erasmus+ Programme of the European Union

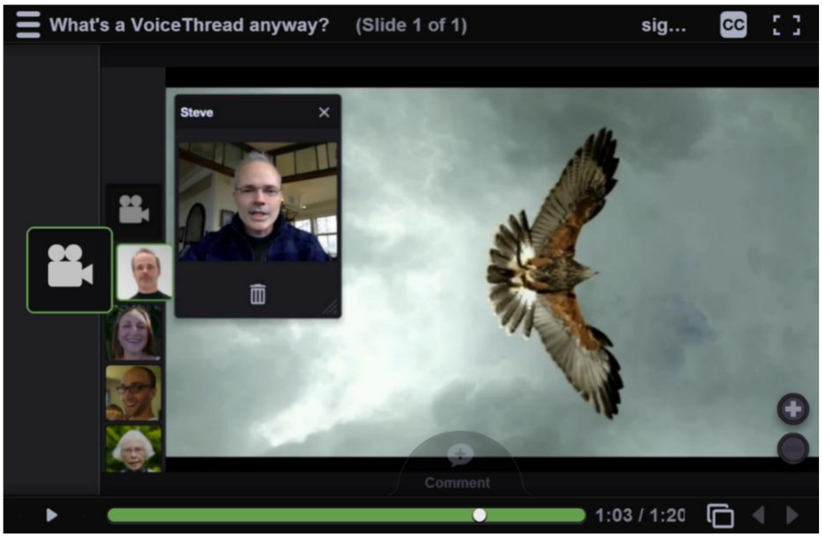

Figure 2: A VoiceThread session.

Both platforms can support online collaborative student activities (e.g., students working on a group presentation). These platforms also use AI to support the collaborative process. Harasim (Harasim 1993) divides the online collaboration process into four main stages:

Stage 1 - Idea Generating

In the Idea Generating phase, learners contribute their own opinions by generating and brainstorming about a subject. This is the stage where learners present their ideas on a predetermined topic or subject.

Stage 2 - Idea Organising

In the Idea Organising phase, students interact with one another; they are exposed to new ideas from their peers. "Learners begin to organise, analyse, and philtre the range of ideas by agreeing or disagreeing with some of the ideas presented, elaborating, expanding, or rejecting others". In contrast to phase one, in this phase of the online collaboration, the learner's perspective of how the topic can be approached from many different viewpoints is expanded due to the diverse input from other peers and the instructor.

Stage 3 - Intellectual Convergence

In the third phase, Intellectual Convergence, learners come to a position on a topic or resolution to the knowledge of a problem. After exchanging ideas on a topic, at this stage, learners reach a consensus or solidify their position, which can be presented as a report, final paper, group presentation, or summary.

Stage 4 - Final Position

The Final Position phase refers to a conceptual change that happens in learners' minds due to the interaction and input in the previous stages of collaboration.

Each stage involves one or more **"collaboration patterns".** We can use these patterns to train virtual agents to support students during the collaborative process. The literature has identified some collaboration patterns. Vizcaino and Du Boulay 2003 presented a simulated student (SS) using various strategies (Vizcaino and Du Boulay 2003). Additional patterns can be mined from carefully designed empirical studies involving students completing **collaborative learning tasks** on a multimedia platform (e.g., VoiceThread of Padlet) with the help of a virtual agent.

Situation	**Role**	**Strategy**
Students do not have enough knowledge so they don't know how to work.	The SS gives hints or explains exercises.	Proposing clues or solutions but always with the goal of fostering students' deflection.
Students always try wrong solutions (perhaps they are trying to guess the solution).	The SS explains why that solution cannot work. The SS tries to motivate the students (if it occurs that students are bored or tired).	To accustom the students to think about the advantages and disadvantages of the proposal.
Students have different view about the solution, and they propose different or even opposing answers.	The SS helps the students to reflect on the different proposals. The SS encourages the student who proposes the solution to explain it.	To teach respect for different ideas and to think about their advantages or disadvantages. Learning by listening and learning by teaching.
Students propose correct solutions.	The SS checks that students really understand the solutions	Checking gain of knowledge.

586297-EPP-1-2017-1-EL-EPPKA2-CBHE-JP
Co-funded by the Erasmus+ Programme of the European Union
The European Commission's support for the production of this publication does not constitute an endorsement of the contents, which reflect the views only of the authors, and the Commission cannot be held responsible for any use which may be made of the information contained therein.

	and that they did not arrive at it by chance. The SS proposes a wrong solution to create doubt.	

Figure 3: Example collaborative patterns (Vizcaino and Du Boulay 2003).

Virtual agents can have the following forms:

1) **A disembodied voice**

Agents can provide contributions like any other member of the group. Such virtual agent can interact with students **asynchronously,** having either an expert or a virtual peer's role. Expert agents can use one or more of the following strategies to support students:

- Collaborative patterns found in the literature (e.g., (Vizcaino and Du Boulay 2003)).
- Pedagogical strategies.
- Productive failure: allowing students to explore a concept and make mistakes before being shown the correct answer.
- Feedback: questions, hints, or haptics, triggered by student actions, which are designed to help the student improve their learning (offered after the student has posted their contribution.
- Assessment to measure learning.

Virtual peer agents can use one or more of the following strategies to support students:

- It appears to be at a similar cognitive level to students.
- Someone who provides alternative points to stimulate productive argument or reflection.
- Use collaborative patterns found in the literature (e.g., (Vizcaino and Du Boulay 2003)).

A virtual peer can also:

- Help smooth the group and problem-solving process, accentuating the positive aspects of group learning and minimising the negative ones.
- They serve as a role model in the PBL process for inexperienced students, facilitating student response and participation from everyone in the group. Peer tutors who were previous

students in the course can reassure and support students, particularly newcomers, when they feel challenged.

- Peer tutors check the content of the discussion, looking for conceptual understanding.
- They also decide when to answer student questions and when to throw questions back to the students.
- Tutors serve as the instructor's window into their groups, informing them of what is working well and what is not. Feedback from peer tutors is very informative to the instructor.
- Add gamification elements to the agent's responses based on the gamification user types Hexad (Tondello, Wehbe et al. 2016).

2) Conversational bot:

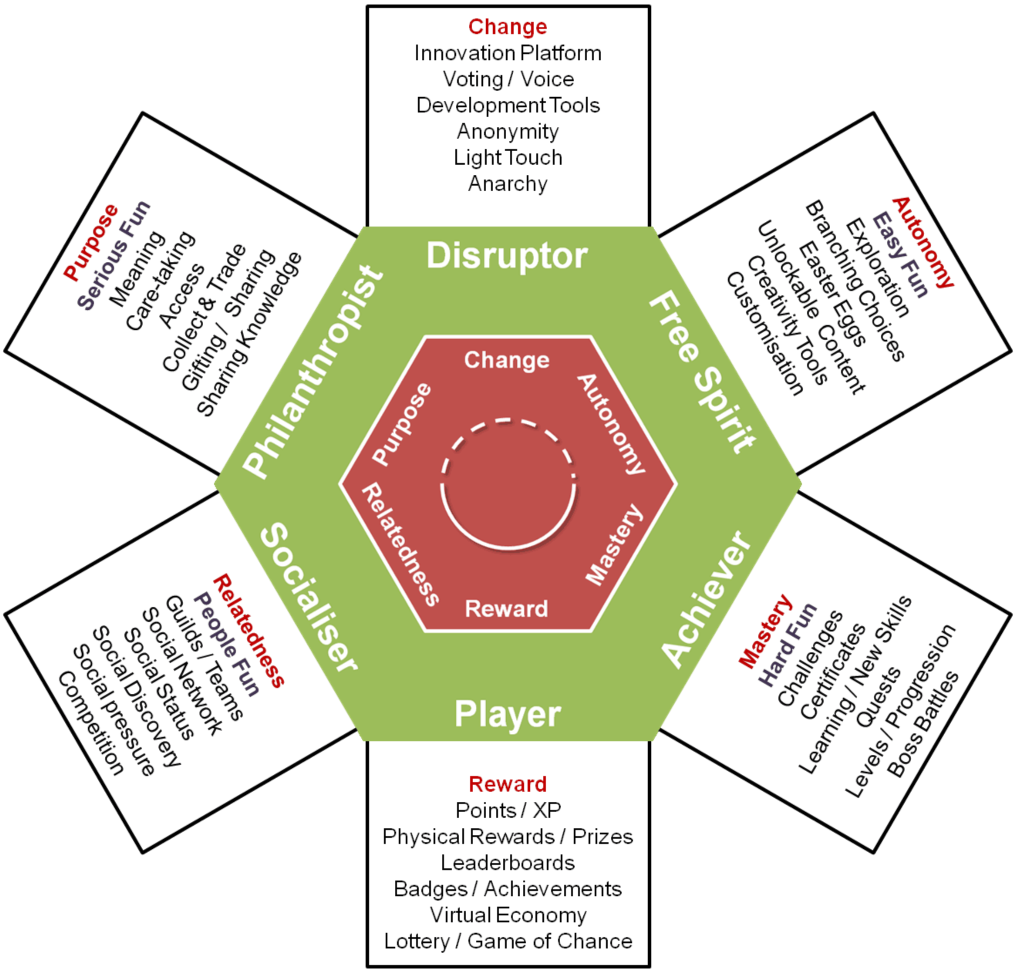

Figure 4: Gamification user types Hexad and characteristics.

Chatbots can provide real-time support to students **synchronously** (see Figure 5). They can be integrated into the collaborative learning space (VoiceThread or Padlet) or the LMS (e.g., Moodle or Blackboard) that hosts it. For a conversational bot to effectively support students, it should meet the following minimum requirements:

- Complete knowledge of collaboration patterns in all stages of the online collaborative learning process.
- It tries to make sense of what the user needs to be based only on user input.

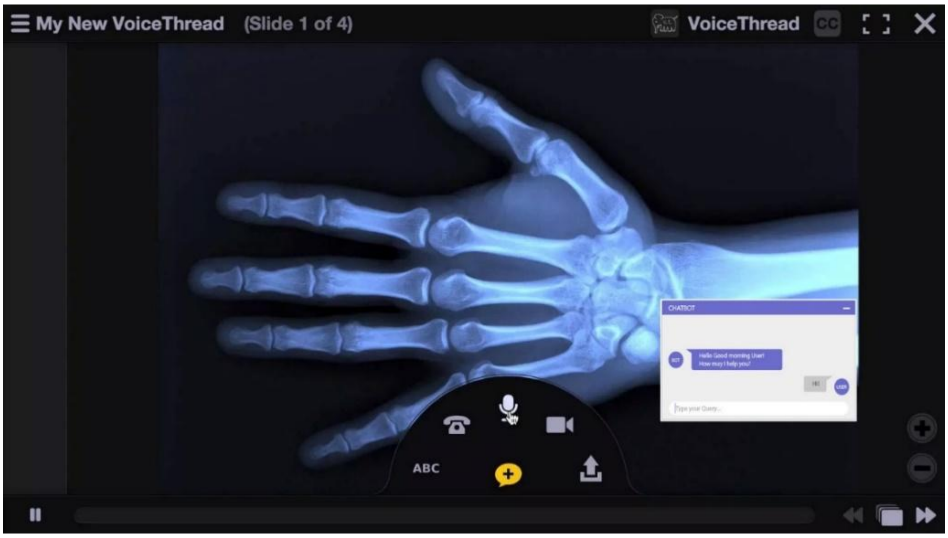

Figure 5: A chatbot integrated into VoiceThread assisting students.

Some of the most commonly used platforms to develop chatbots are:

- IBM Watson Conversation[2].
- Amazon Lex[3].
- Dialogue Flow[4].
- Rasa[5].

[2] https://www.ibm.com/cloud/watson-assistant/

[3] https://aws.amazon.com/lex/

[4] https://dialogflow.cloud.google.com/#/getStarted

[5] https://rasa.com/

586297-EPP-1-2017-1-EL-EPPKA2-CBHE-JP

3) Embodied Conversational Agents (ECAs)

An Embodied Conversational Agent (ECA) can be embedded in online conversations either as a video or a 3D avatar (see Figure 6). The ECA can have the role of an expert or a virtual peer interacting asynchronously with students. For an ECA to effectively support students, it should meet the following minimum requirements:

- Consume multimedia content generated by students and tutors during the collaborative learning process using AI technologies (e.g., video AI) to build its domain expertise in real-time.
- Knowledge of the learner. The chatbot should have at least some knowledge of the learner (e.g., previous achievements and difficulties, engagement in learning).
- Emotion recognition (based on textual responses).

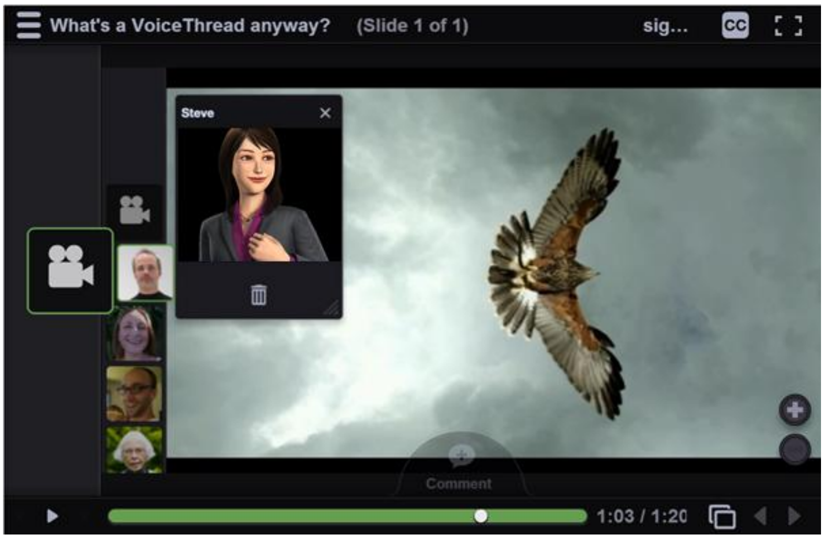

Figure 6: VoiceThread with an ECA embedded in the conversation.

It is also possible to apply AI on these platforms to generate **smart content (SC).** SC uses AI to condense textbooks into a more digestible study guide with chapter summaries, practice tests and flashcards.

3.2 Physical Classroom

In physical classrooms, students interact with an ECA using either a standard computer with a webcam and microphone or a large display (e.g., a smartboard).

3.2.1 Rapport ECAs

Students complete tasks in such a learning environment in collaboration with the teacher and an ECA “living” on a desktop computer (see Figure 7). Such an ECA can detect students’ emotional state and react with appropriate verbal and non-verbal behaviours (Jang 2018) to create rapport. A rapport ECA can have a positive impact on the student’s learning experience:

- The teacher’s role in the process (engage the whole class with the task).
- Because of emotional intelligence and adaptive behaviours, users will eventually exhibit contingent behaviours with the ECA. It should further strengthen the teacher’s positive influence and enable users to create rapport with the ECA.
- It is known that creating rapport is related to better learning outcomes.

Figure 7: A rapport ECA

3.2.2 Multiple Embodied Conversational Agents (ECAs)

In this learning environment, students can interact with multiple ECAs (an ECA acting as a group facilitator, another as the teacher and two more ECAs representing students). As opposed to the first scenario, teachers and students interact in a virtual reality environment. A dialogic learning scenario can help teachers cultivate dialogic skills in students (e.g., participating in debates). It is possible to implement different facilitation models in the ECA according to a dialogic learning scenario (e.g., Full facilitator, teacher-driven and Context-driven) (Doumanis and Economou 2019).

Co-funded by the Erasmus+ Programme of the European Union

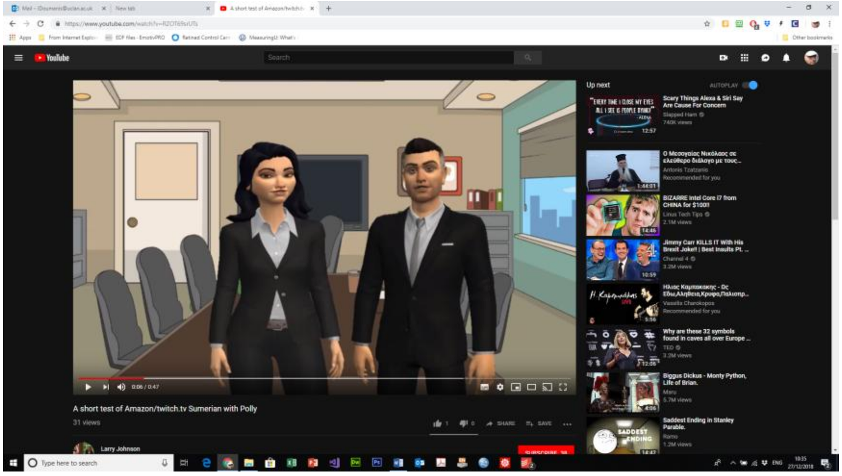

Figure 8: Multiple ECAs.

3.3.3 Life-Size ECAs

Life-size ECAs can be embedded in the classroom (e.g., on a smartboard or a big display) (Services 2018)). They can facilitate multiple collaborative learning scenarios where students, teachers and the ECA work on a common problem.

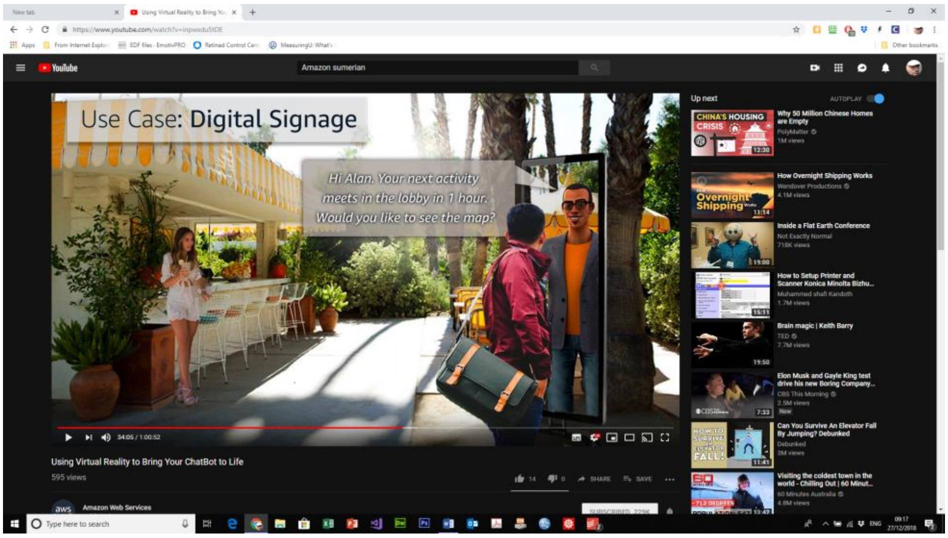

Figure 9: A life-size ECA integrated into the physical environment.

An ECA can be automated using AI algorithms or puppeted by a wizard (Marge, Bonial et al. 2017). In Wizard of Oz (WoZ) scenarios, the Wizard has full knowledge of what is going on in the classroom through a live video feed. Multiple learning scenarios can be tested with the ECA in a teacher's assistant role (e.g., a trainee lawyer to teach law students).

3.3 Collaborative Virtual Environments (CVEs)

In these learning environments, students interact with ECAs in immersive collaborative virtual environments (CVE).

3.3.1 Role-playing simulations

CVEs can facilitate role-playing simulations. In these simulations, students take a role and interact with ECAs in learning scenarios designed to achieve specific learning outcomes. For example, in the role-playing simulation of Figure 10 (Economou, Doumanis et al. 2016), the student plays a lawyer who tries to determine the type of crime the client has committed. The simulation can be extended to include multiple students working collaboratively in different roles (e.g., an experienced lawyer and a trainee).

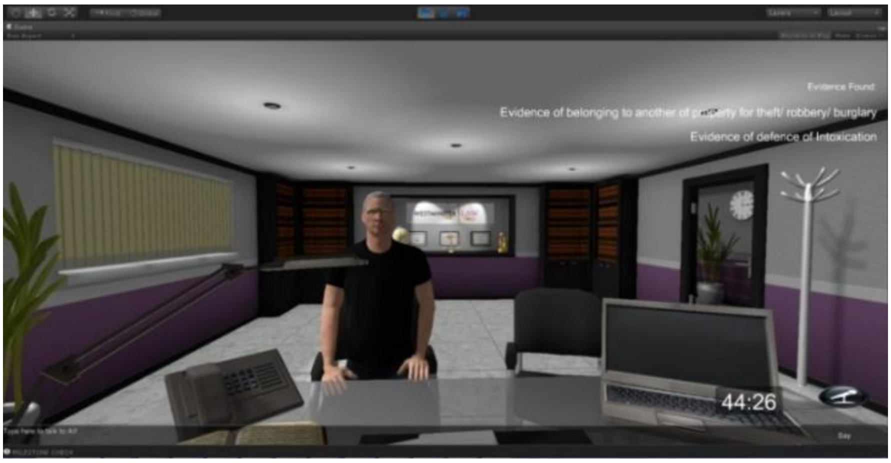

Figure 10: The legal scenario of the WMIN platform

3.3.2 Full-body immersion

It is possible to fully immerse users in CVEs using a full-body VR suite (TESLASUIT 2019). This type of suite enables users to feel the presence of other students and ECAs in the CVE, which can impact their immersion. They also include biometric sensors, which can support gathering deeper insights about the experience of students.

3.4 Augmented Reality experiences

In AR experiences, students interact with AR content, including virtual agents using a mobile device (mobile phone or tablet) or AR glasses (e.g., Magic Leap[6]). The learning scenarios below include standard AR content as well as virtual agents (embodied or otherwise).

3.2.1 AR Experience in the classroom

AR can support experiential learning in the classroom. Figure 11, shows a child interacting with 3D content projected on the Holocube, a toy designed to project 3D content and interactive simulations. It is possible to build experiential learning scenarios where two students (one using a headset and another a standard mobile device) work together to achieve a learning task (e.g., to build a water molecule)

Figure 11: A child interacting with AR content.

3.4.2 Outdoor social mini games

These outdoor social mini-games can support collaborative learning activities in the field. They can be designed as interactive storytelling games with virtual agents working on a par students to achieve learning goals. The design of the mini-games should meet the following minimum requirements:

[6] https://www.magicleap.com/

- Be a localised learning experience.
- Promote student collaboration.
- Fully interactive and personalised learning experiences.
- Interactive Storytelling.

Mini-games should offer fully localised content (e.g., matching specific locations in a city). They are multi-player experiences requiring students to work collaboratively to complete tasks. For example, the game may require players to work together on solving a puzzle by manipulating objects (rotate and dragging them) in the physical environment. These mini-games can be integrated into interactive stories with virtual agents providing an immersive experience tailored to players' location and preferences.

3.5 Mixed reality classrooms

In these environments, students can interact with life-size virtual agents (see Figure 12) and the physical environment to achieve learning tasks. CGI content can also interact with the physical environment. One-on-one scenarios are the simplest to implement, but more complex scenarios with multiple students interacting with multiple virtual agents and each other are also possible.

Figure 12: A human interacting with a life-size virtual human.

Recent technological developments (e.g., Magic Leap) enable educators to create experiential learning scenarios simulating various real-world learning environments. These environments include a mixture of physical objects and CGI content interacting with each other. For example, it is possible to build a mixed reality lab for medical students where they can participate in simulated surgeries. Students can use physical objects (e.g., surgical tools) while interacting with virtual agents, students and the instructor to achieve learning tasks.

3.6 One-on-one tutoring

It is known that one-on-one human tutoring has a significant effect on improving learning outcomes. The study, reported in (BLOOM 1984) found this type of learning intervention to be the most efficacious of a set of learning intervention methods tested on students. However, one-on-one tutoring can never be attainable for all students. No educational institution can afford to provide a human tutor for every learner. It is possible to use virtual agents to make one-on-one tutoring available to all learners regardless of the subject. Such virtual agents can utilise a range of conversational (Angel 2016) and instructional tutoring strategies (Frey and Reigeluth 1986) to support students. These strategies include conversations as dialogue and structured materials designed to lead learners in small steps. Virtual agents designed for one-on-one tutoring are usually standalone systems. Virtual tutors integrate the following components:

- An NLP (Natural Language Processing) component used to interpret student utterances and provide appropriate responses.
- A conversational component designed to simulate various conversational and instructional tutoring strategies.
- A personality expressed through the conversation.
- Relevant learning content (e.g., videos and animations) to support the tutoring process.

There are some commercial solutions in the market (e.g., Watson tutoring in Figure 13). However, the proprietary nature of these products makes it challenging to implement new conversational and instructional tutoring strategies. It is possible to build custom virtual agents utilising state-of-the-art tools (e.g., Amazon Lex) to simulate one-to-one human tutoring, delivering tailored activities and timely feedback matching the learner's cognitive needs, all without the instructor's assistance.

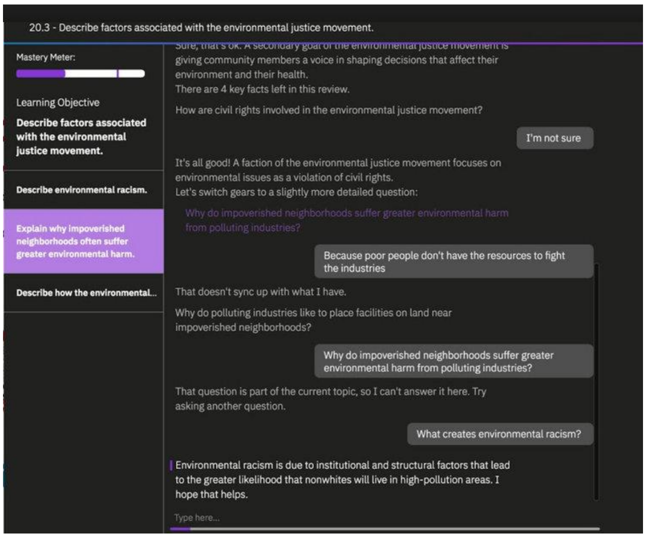

Figure 13: Watson Tutor (Standalone system)[7].

Virtual agents for one-on-one tutoring can support various collaborative learning scenarios both in class and outside the classroom. One possibility is to support instructors in delivering mini-lessons during an in-class problem-based learning (PBL) activity with many students. During the session, the instructor can assign students to either human or virtual tutoring groups. This way, the instructor can support all students, which would have been difficult to achieve in a regular PBL session.

4. Evaluation of Collaborative Learning Experiences

We suggest biometric methods as a way to evaluate applications of virtual agents in collaborative learning environments. Biometric research methods capture signals from the body using various sensors (e.g., eye-tracking and Electroencephalography (EEG). Using biometrics, it is possible to assess mental workload, emotions, and other relevant learning cognitive or sub-cognitive processes. Below we discuss some ideas on how to evaluate aspects of learning in prototypes with virtual agents.

4.1 Assessing cognitive load during collaborative learning tasks

This is about measuring students' cognitive load during online collaborative learning tasks (see (Mills, Fridman et al. 2017) for a similar study). It is possible to run studies manipulating various aspects of the collaborative task (e.g., difficulty vs easy), background knowledge of learners and

[7] http://www.caitlinmacrae.com/ibm-watson-tutor-1

virtual agent tasks (virtual agent-assisted task vs non-virtual agent-assisted task). It is also possible to start with simple studies that require users to produce minimal multimedia elements (e.g., images and audio) on a platform like VoiceThread without any AI assistant. Such studies can establish a baseline on the possible effects of the various instructional technologies on users' cognitive load when completing collaborative learning tasks online.

4.2 Measuring the emotional state of students during collaborative learning tasks

This is about assessing the user's emotional state during online collaborative learning tasks. As above, it is possible to run multiple studies manipulating various aspects of the experience. It is also possible to start with simple studies that require users to produce minimal multimedia elements without the assistance of virtual agents. Such studies can establish a baseline on the possible effects of various instructional technologies on users' emotions when completing collaborative learning tasks online.

Both types of studies can generate knowledge that can ultimately lead to training learner models for virtual agents to better support students when completing online collaborative learning tasks. The same approach can be applied to one-on-one tutoring systems.

4.3 Analysing biometric data

There are three methods to analyse biometric data to gain insights into the cognitive processes and sub-processes involved in learning.

1) Raw biometric data

This is about processing raw biometric data to map neural activity (e.g., captured using EEG) to mental processes manually. It is possible, for example, to compare temporal data (voltage over time) of a user (or all users) when exposed to a stimulus over when exposed to a different stimulus. Conclusions on the learner's cognitive state are based on channels that gave data of interest and support from the literature.

586297-EPP-1-2017-1-EL-EPPKA2-CBHE-JP
Co-funded by the Erasmus+ Programme of the European Union
The European Commission's support for the production of this publication does not constitute an endorsement of the contents, which reflect the views only of the authors, and the Commission cannot be held responsible for any use which may be made of the information contained therein.

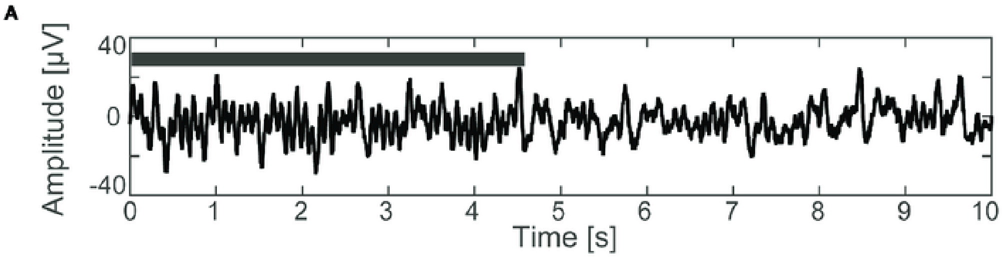

Figure 14: An EEG graph of voltage (μV) over time (s).

A workflow (e.g., such as the workflow presented by FEDA (Halford, Shiau et al. 2015)) can streamline the process. The workflow includes all the necessary stages to process the data (e.g., cleansing of the data). Overall the process is labour-intensive and may not be suitable for education purposes.

2) Data processing using machine learning algorithms

This is about using classifiers to map raw EEG data into cognitive states of interest automatically. The process is as follows:

- Apply the selected steps of Feda's workflow (Halford, Shiau et al. 2015) to the raw EEG data (e.g., the data cleansing stages is essential).
- Apply Frequency-based analysis to raw EEG data (e.g., Fast Fourier Transform). This will convert the raw EEG data into the frequency domain (see Figure 15).
- Apply a machine learning classifier (e.g., QStates for cognitive state classification (J McDonald and Soussou 2011)) on the EEG data to automatically detect the desired cognitive state for the whole duration of a specific stimulus.

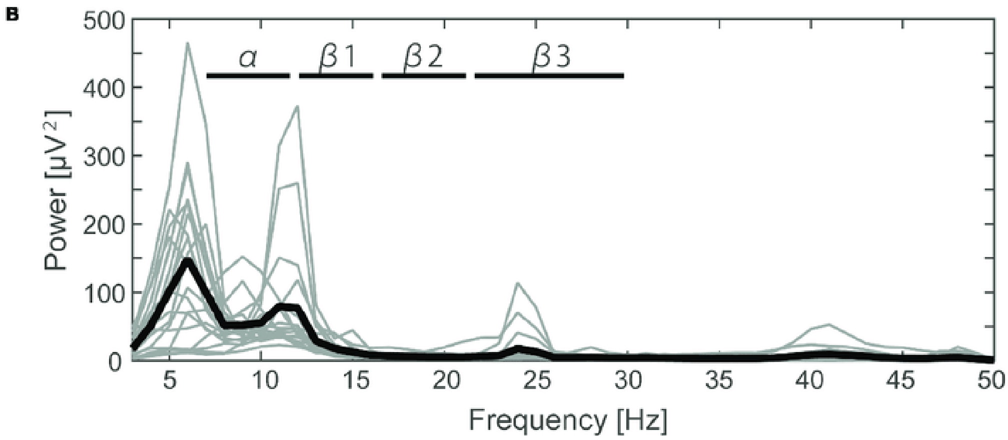

Figure 15: An EEG graph of voltage (μV) over frequency.

3) Compute performance metrics in real-time

This is about using software (e.g., Emotiv Pro[8]) to compute performance metrics in real-time. The software uses algorithms that classify raw EEG data over time for specific performance metrics (e.g., stress, engagement).

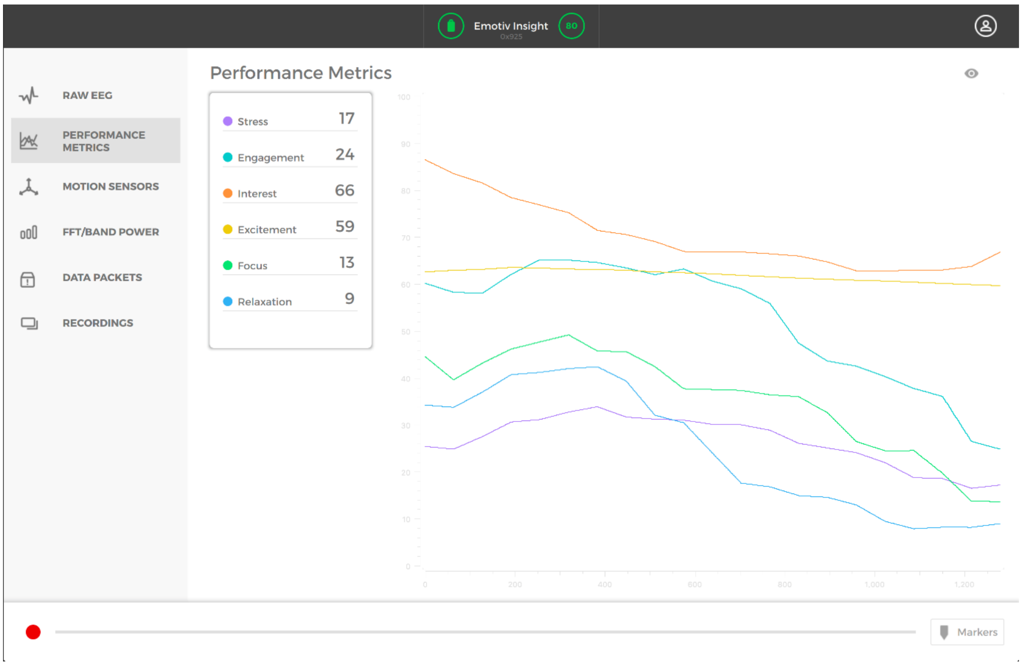

Figure 22: Performance Metrics using EmotivPro software

Below we discuss some important metrics (Emy 2019):

- **Stress (FRU)** is a metric for how happy a learner is with the present situation. A highly stressful situation can result in an inability to complete a task. In general, a low to moderate level of stress can boost productivity, while a higher level can be harmful and have long-term health implications.
- **Engagement (ENG)** measures how immersive a learner is at a given moment. Involvement can be described by increased physiological arousal and beta waves as well as attenuated alpha waves. The more attentive and focused learners are to a task, the greater is their engagement.

[8] https://www.emotiv.com/emotivpro/

- **Interest (VAL)** measures how attractive or aversive a learner finds the task. Low interest indicates a strong dislike for the task, high interest indicates a strong affinity for the task, and mid-range scores suggest that you are undecided about the activity.

Computing performance metrics during an evaluation is the best approach from an educational perspective. As the software produces timestamp data, it is also straightforward to map EEG with other signals (e.g., eye-tracking) to learn more about participants' visual activity while interacting with the virtual agent.

5. Conclusions

This report outlines PBL and the history of AI demonstrating how AI has been applied in a wide range of collaborative learning contexts. With the advancement of technology including speech recognition, augmented reality application infused with AI capabilities are on the rise. This report showcased and critiques a number of these including VoiceThread and Magic Leap. These platforms have the potential to help facilitate collaboration through the use of AI to interact with the learning offering guidance and feedback on their learning experience.

The final sections of this report outline some of the possibilities for evaluating technology that incorporate AI. Within education there is a long history of using surveys for student feedback but here we are discussing the use of physiological measures that remove the subjective interpretation from the data. This data could also be used to improve the AI capabilities as constructs such as stress, anxiety and enjoyment could be captured and the students experience could be adapted based upon the use of this data.

Overall there has been a rise in the number of educational application embedding AI capabilities in order to improve the experience and learning of the student. Collaborative learning within engineering disciplines is important and AI has the ability to offer personal support and guidance using synchronous forms of communication with conversational agents. These technologies have the opportunity to enrich and enhance the educational experience of students studying engineering course around the world.

586297-EPP-1-2017-1-EL-EPPKA2-CBHE-JP

Co-funded by the Erasmus+ Programme of the European Union

The European Commission's support for the production of this publication does not constitute an endorsement of the contents, which reflect the views only of the authors, and the Commission cannot be held responsible for any use which may be made of the information contained therein.

References

Angel, D. W. (2016). "The Four Types of Conversations: Debate, Dialogue, Discourse, and Diatribe." from https://medium.com/@DavidWAngel/the-four-types-of-conversations-debate-dialogue-discourse-and-diatribe-898d19eccc0a.

BLOOM, B. S. (1984). "The 2 Sigma Problem: The Search for Methods of Group Instruction as Effective as One-to-One Tutoring." Educational Researcher **13**(6): 4-16.

Doumanis, I. and D. Economou (2019). Affective Communication between ECAs and Users in Collaborative Virtual Environments: The REVERIE European Parliament Use Case.

Economou, D., I. Doumanis, F. Pedersen, P. Kathrani, M. Mentzelopoulos, V. Bouki and N. Georgalas (2016). "Westminster Serious Games Platform (wmin-SGP) a tool for real-time authoring of role-play simulations for learning." EAI Endorsed Trans. Future Intellig. Educat. Env. **2**(6): e5.

Emy. (2019). "What are the Performance Metrics Detection Suite?", from https://www.emotiv.com/knowledge-base/what-are-the-performance-metrics-detection-suite/.

Frey, L. A. and C. M. Reigeluth (1986). "Instructional models for tutoring: A review." Journal of instructional development **9**(1): 2-8.

Halford, J. J., D. Shiau, J. A. Desrochers, B. J. Kolls, B. C. Dean, C. G. Waters, N. J. Azar, K. F. Haas, E. Kutluay, G. U. Martz, S. R. Sinha, R. T. Kern, K. M. Kelly, J. C. Sackellares and S. M. LaRoche (2015). "Inter-rater agreement on identification of electrographic seizures and periodic discharges in ICU EEG recordings." Clinical neurophysiology : official journal of the International Federation of Clinical Neurophysiology **126**(9): 1661-1669.

Harasim, L. (1993). "Collaborating in Cyberspace: Using Computer Conferences as a Group Learning Environment." Interactive Learning Environments **3**(2): 119-130.

J McDonald, N. and W. Soussou (2011). QUASAR's QStates cognitive gauge performance in the cognitive state assessment competition 2011.

Jang, A. N. a. J. (2018). "Amazon Sumerian Concierge Experience." from https://docs.sumerian.amazonaws.com/articles/concierge-experience/

Kek, M. and H. Huijser (2011). “The power of problem-based learning in developing critical thinking skills: Preparing students for tomorrow’s digital futures in today’s classrooms.” Higher Education Research & Development **30**: 329-341.

Marge, M., C. Bonial, B. Byrne, T. Cassidy, A. W. Evans, S. G. Hill and C. Voss (2017). “Applying the Wizard-of-Oz technique to multimodal human-robot dialogue.” arXiv preprint arXiv:1703.03714.

Mills, C., I. Fridman, W. Soussou, D. Waghray, A. M. Olney and S. K. D’Mello (2017). Put your thinking cap on: detecting cognitive load using EEG during learning.

Services, A. W. (2018). “Using Virtual Reality to Bring Your ChatBot to Life.”

TESLASUIT. (2019). "TESLASUIT." from https://teslasuit.io/.

Vizcaino, A. and B. Du Boulay (2003). Using a simulated student to repair difficulties in collaborative learning.

Co-funded by the Erasmus+ Programme of the European Union