

Technologies Facilitating Smart Pedagogy



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Abstract This chapter analyses the learning principles governing the learning theories of blended learning, personalized learning, adaptive learning, collaborative assisted learning and game-based learning towards capturing requirements of these theories that can be successfully met and aspects that can be significantly facilitated by technological solutions. We also present a generic learning process structure that can model the above learning theories along with a prototype implementation. The end goal is to showcase the beneficial use of technological solutions in pedagogy.

Keywords Personalized learning · Adaptive learning · Affect detection · Technology-enhanced learning

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1 Introduction

The results of pedagogy, i.e. of the principles and practices of teaching, highly depend on the adopted learning approaches. While pedagogical principles change at a very slow pace mainly due to human nature, the available technologies do change very fast providing different tools to pedagogists. However, teachers do not necessarily follow technological evolution, and computer scientists are not necessarily aware of the benefits that specific developments could bring in education. For our society to make the most out of technology for pedagogy, pedagogists and technology experts have to be brought together. For example, for the learning process to be effective, in the direction from the teachers to the learners, the learning materials should be attractive and tailored to the needs and characteristics of the target student group; in the opposite direction, accelerating the reception of feedback in terms of performance and affect state would help teachers adapt the learning process accordingly.

Different classifications of learning approaches are possible depending on the selected classification factors such as the structure/environment (formal vs non-formal and informal education) and the dominant learning material means (e.g. electronic books/tools/games vs traditional hardcopy books). In all cases, the aim of technology providers is to assist the process and help teachers easily design pedagogical processes, quickly develop learning materials that are attractive to the targeted audience and offer an unprecedented experience as learning is nowadays a lifelong activity, and thus the relevant market is huge and growing.

In this chapter, we briefly discuss different learning approaches and explore the point where technology could bring an added value which ends up realizing that detecting the affect state of the learner is an important step in the learning process irrespective of the learning approach. A flexible learning experience model that can accelerate curricula building, learning material reuse and non-linearity implementation is then described followed by its implementation in a prototype which has been developed in the framework of the H2020 MaTHiSiS project (MaTHiSiS, 2018). The capability to detect affect using face recognition is showcased, and finally an example application use case is presented.

2 Technological Requirements of Diverse Learning Models

Despite the fact that there is no one strict definition of *blended learning*, the term is commonly used in order to describe teaching methodologies combining the traditional face-to-face learning activities with online learning experiences (Garrison & Heather, 2004). In many cases, terms like hybrid, mixed or integrative are used to describe the same trend. Blended Learning is commonly defined as a combination of instruction from two historically separate models of teaching: the traditional face-to-face and the distributed learning systems. In the past, these two learning

models have used different materials and methods, and they have focused on the needs of different target groups. On one hand, face-to-face learning uses teacher-centred environments based on synchronous interactions between persons. On the other hand, distributed computer-based systems emphasize a self-paced distant learning model operated in an asynchronous way. The evolution of technological innovations during the last decades had a huge impact on the possibilities for learning in a distributed environment. Nowadays, the available communication technologies allow us to have real-time synchronous distributed interactions similar to face-to-face environments. So, a blended learning system supports human interaction providing tools, such as real-time virtual collaboration software, self-paced web-based courses, electronic performance support systems (EPSS) embedded within job-task environment and knowledge management systems, but also aims to make machines and computers behave in a more human way. Consequently, the design of such a hybrid teaching activity is a highly challenging process, and it can't be simply addressed by just adding computers in a classroom. In fact, the most difficult part of the above process is that it requires reconsidering the way of thinking from the teacher's and also from the student's side. Blended learning approach is based on the idea that learning is not a onetime process but a continuous process.

Personalized learning refers to educational programs which intend to address special educational needs of specific student groups. In the traditional teaching model, within a classroom, the educator may provide to all students the same lecture, the same material, textbooks, assignments, etc. with little variation from student to student. On the contrary, personalized learning follows a student-centred approach, since the main goal is to make the individual learning needs the primary consideration during the learning process. So, the personalized learning approach aims to provide an optimal learning path to academic success of each student first by determining the learning needs, interests, prior background and aspirations of individual students and then by providing learning experiences that are customized for each student. Personalized learning models started from web-based tutoring applications providing a great quantity of learning material (Berghel 1997; Borchers, Herlocker, & Riedl, 1998). Next, in order to increase the efficiency of the learning process, personalized guidance mechanisms based on mechanisms for adaptive content navigation/presentation and also student's intelligent analysis have been proposed (Chen, Lee, & Chen, 2005; Tang & Mccalla, 2003; Weber & Specht, 1997). In our days, modern personalized systems consider the learner's preferences and interests and investigate the learner's behaviour in order to create a continuously adapting learning environment based on the interaction with each one of the learners (Lee, 2001; Papanikolaou & Grigoriadou, 2002; Tang & Mccalla, 2003). In general, a personalized learning environment can be considered to be any platform in which the learner expresses his/her learning requests and knowledge background, and the material is presented in a way that takes advantage of the learner's learning preferences (Steed, 2002).

Adaptive learning is based on the idea of designing learning methodologies to address student's specific learning preferences and needs. The concept is that an individualized method of teaching will help students to understand better and learn

faster (Jones & Jo, 2004). The first development attempts of adaptive learning environments were targeting either small groups of learners or a very limited area of interest. This is due to the fact that these earlier implementations provided a very basic adaptivity model. In our days, adaptive learning platforms have evolved rapidly using innovative computer technologies, such as data mining, artificial intelligence, etc., in order to deliver customized material per student. The platform profiles each learner by monitoring his/her behaviour, tracking the level of his engagement and identifying his requirements, preferences and background in order to adapt the learning process to provide specific knowledge as and when it is required (Paramythis & Loidl-Reisinger, 2004). A modern adaptive learning platform is able not only to identify each learner's current knowledge level but also determines the activities, the sequence and the medium in order to maximize student's academic success. In fact, in a modern learning platform, both personalized and adaptive approach can be complementarily combined. The personalized-based techniques can be used in order to determine the main learning milestones that each individual learner needs to accomplish in order to succeed. But the "learning path" (content, activity types, sequence, etc.) that each learner is going to follow from milestone to milestone is different, and it can be modified dynamically during the learning process based on the adaptive learning techniques.

Collaborative learning assumes that the knowledge does not exist somewhere waiting to be discovered, but it is socially produced when a group of two or more parties interact with each other in the learning process. In general, the term collaborative learning refers to learning activities specially designed to be executed from pairs or small interactive groups. But, just assigning learners to groups does not guarantee that they will collaborate with each other (Brush, 1998; Soller, Lesgold, Linton, & Goodman, 1999). In this context, the instructor's responsibility is first to design the tasks of the learning activities in a way that promotes the interaction in the group and second to become a member of a team searching for the knowledge rather than the authority which provides it. This learning approach helps the learners to achieve a deeper level of learning as well as to develop their critical way of thinking (Garrison, Anderson, & Archer, 2001; Johnson & Johnson, 1999). Additionally, this approach provides an environment in which group members can improve their social and communication skills and build positive attitudes towards co-members and the learning process (Johnson & Johnson, 1989). However, parameters like group size, group composition, learning preferences, etc. have been identified as factors that have an impact on the effectiveness of collaborative learning, and they are summarized under the term of "social interaction" (Hooper & Hannafin, 1991). Many researchers believe that social interaction plays a very critical role in collaborative learning because any kind of collaboration is based on it (Johnson, Johnson, & Stanne, 1985). Researchers (Kreijns, Kirschner, & Jochems, 2003) discuss three approaches to stimulate the collaboration within groups: the cognitive approach of promoting "epistemic fluency", the direct approach of structuring task-specific learning activities and the conceptual approach of applying a set of conditions to stimulate/stress collaboration. Further discrimination of collaborative

learning cases with respect to the competence level of each learner is also discussed in the next section.

In many cases the usage of technology (e.g. web-based learning materials) in the learning process is not enough to motivate students, especially the younger ones and those who had lived in the midst of technology all their lives. One approach to enhance their engagement is to introduce computer games in education (Norman, 1993; Martin & Reigeluth, 1999). A game-based learning application creates a virtual environment that looks and feels familiar, within which learners can make mistakes at no risk, practise through experimentation on things and learn to do things in the right way. This approach keeps learners highly engaged in practising through tasks that can be easily transferred from a virtual to real life. However, in order to maximize the effectiveness of an educational game-based platform, both dimensions of educational goals and gameplay experience must be carefully balanced. In Rollings and Adams (2003), authors discussed several types of challenges that can be applied to educational games. Designers of educational games should also pay attention to the appearance of the game, an engaging storyline and the appropriate game balance in order to involve players (Killi, 2005). There is no doubt that people do learn from games; the open issue is how to design games in a way that people learn what they need to learn. To achieve this goal, we need generally effective techniques, processes and procedures for designing games that reliably achieve the intended instructional objectives (Tobias, Fletcher, & Wind, 2014).

3 Affect Detection for Effective Learning

Research has shown that maintaining high levels of student engagement during the learning procedure can significantly determine successful learning (Iovannone et al., 2003) (Carpenter et al., 2015; Hargreaves, 2006). Effective personalized learning was shown to encourage participation and engagement, not only in the classroom but also in extracurricular clubs and work-related learning (Sebba, Brown, Steward, Galton, & James, 2007). As the tutor forms a better understanding of their pupils' strengths and challenges, they are in a better position to consciously plan their scaffolding objectives and choose the interaction media while preserving the pupils' interest and engagement (Dolan & Hall, 2001). Classroom-related affective states are linked to the students' goal structure and their adoption of specific achievement goal orientations. The goal to learn and understand is associated with an increase in positive emotions like enjoyment of learning as well as a decrease in negative emotions like boredom. The relation between goals and affect, however, is a reciprocal one as proposed in Linnenbrink and Pintrich's bidirectional model (Linnenbrink & Pintrich, 2002). In 2002, Linnenbrink and Pintrich described a model of affect in which performance is reciprocally related to the learner's mood (Pekrun & Linnenbrink-Garcia, 2014). In this model, the learners' personal goals are highly influenced by their perception of challenge. This perception in turn has a direct influence on their affect state. Based on the larger literature, positive moods

like learner's interest and their active engagement are thought to support greater performance, while negative moods lead to performance degradation.

This relationship dictates the quality of learning where positive moods encourage a greater result and negative moods encourage less learning or learning abandonment. This relationship has also been described in more detail in the Mihaly Csikszentmihalyi theory of flow (Shernoff, Csikszentmihalyi, Schneider, & Shernoff, 2014), where skill and task challenge perception can launch someone in a variety of emotions. Importantly, it has been argued that not all emotions are relevant to educational context or when the learner requires scaffolding intervention. It was Sidney D'Mello and Rosalind Picard (D'Mello, Picard, & Graesser, 2007) who conducted a study on the relevance of emotions to learning in an e-learning tool and found that they could quantify the most relevant emotions to skill acquisition as "frustration", "boredom" and "flow". Only later in 2013, a study (Basawapatna, Repenning, Koh, & Nickerson, 2013) combined learner skill, independent learning limit and scaffolding in a state change diagram (Fig. 1). This diagram depicts the relationship between perception of challenge, the affect state of the learner and their performance. Greater performance happens where the task difficulty is just slightly above the learner's skill level, and it is where optimal learning occurs. Critically, this work provided the first state change diagram that shows the relationship between the learner's affect state and their learning potential and the relationship it has with the perception of difficulty or challenge.

The learner's performance or skill level is displayed as the X-axis, and the task challenge is displayed as the Y-axis. This diagram can be used to track the learner's progress in a learning activity. In this way, the diagram can represent any permutations of level of skill or task difficulty. Ideally, the optimal learning path must take the learner through what Vygotsky named the "zone of proximal development" (called hereafter ZPD) (Chaiklin, 2003). This is the optimal level of arousal and where learning challenge perception is just slightly more difficult than the learner's

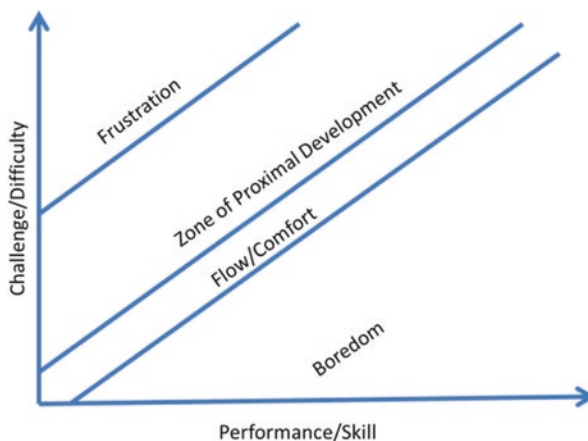


Fig. 1 Zones of proximal flow

current skill level. In this state the affective state would have the learner in an engaged and interested state of mind. In turn, this promotes greater learning opportunities and an affective state or mood that encourages higher aims and goals. It is important to note that the optimal learning experience would try to avoid both boredom (challenges that are too easy) and frustration (challenges that are too difficult) to maximize engagement.

3.1 Adaptive Learning

To achieve optimal learning, a dynamic learning approach must be adopted which considers both the learner's affect state and their performance – then in return *adjust the learning material challenge to maintain the positive mood of the learner* where the learner's ambitions for goal achievement and subsequently the learner's performance are maximized. The system will then lower or raise the difficulty of the learning material challenge to a level where the learner's affect state is engaged (in the ZPD) and their performance is always improving. The system would continuously monitor both *affect state and performance* to maintain this delicate balance. The learner state of affect must, however, be continuously monitored to avoid projecting the challenge too high and making the user “frustrated” or too low which would make the learner “bored” (as visualized in Fig. 1). Conclusively, the outcome of this process is the new concept of materialization in the learner's mind and learning which has been achieved, adding to the learner's skill base and progressing them on the graph higher and higher and further to the right.

3.2 Collaborative Learning

In educational research and developmental psychology, there has been a move away from seeing the learner as a lone individual to recognizing the importance of social interaction and seeing learning as a distributed process (Luckin, 2010). One of the theoretical underpinnings of MaTHiSiS is the sociocultural learning models of Vygotsky and his concept of the ZPD. Collaboration is key to the ZPD, and it is often interpreted as between a teacher or more experienced learner and a less experienced learner. However, such collaboration would also be possible between two learners of similar experience. Authors (Ghou, Chan, & Lin, 2003) describe this as the companion to an educational agent. Luckin (2010) goes on to explain that participants develop a shared understanding through the use of mediating tools. According to (Damon & Phelps, 1989), three types of peer-based instruction need to be distinguished: peer tutoring, cooperative learning and peer collaboration. A somewhat different categorization is described by Boyle, Arnedillo-Sanchez, and Zahid (2015) who designed a multi-user collaborative game using gestural interaction to provide autistic children with a means to build, practise and consolidate their

joint attention skills. The authors describe three different collaboration patterns: passive sharing pattern, where users engage with their own objects; active sharing pattern, where users begin to select from shared resources; and active sharing and joint performance pattern where users must build on their turn-taking skills to assist each other. Similarly, collaborative learner approaches have been the focus of attention in many works, as well. Grasha-Reichmann has enumerated a learner's role in a collaborative learning experience (Oray, 2010; Ford, Robinson, & Wise, 2016) as "avoidant", "participant", "competitive", "collaborative", "dependent" and "independent". These roles can be recognized and used to coordinate compatible learning groups or learning pairs that best nurture successful peer-to-peer scaffolding opportunities.

However, successful cooperation is not always guaranteed. Although the first consideration here is that learners will automatically become more involved, thoughtful, tolerant or responsible when working with others, there is considerable and disturbing evidence that students often do not behave prosocially. If not handled correctly, dysfunctional interactions can occur between learners such that low achievers can feel stigmatized and differences in status can be exacerbated (Beaumont, 1999; Blumenfeld, Marx, Soloway, & Krajcik, 1996; O'Connor & Jenkins, 1996). A second consideration is that giving help is not straightforward and conventionally is the responsibility of the teacher. It may not come easily to a peer. Collaborative learning involves both giving and seeking help, and it is believed that help-giving can benefit not only those receiving it but also those giving it. However, help givers can feel frustrated. They may not know how to help effectively and may require special training to learn how to elaborate their thinking such that it benefits their partner. Their partner may not be aware that they need help nor seek it when needed because they believe that needing help indicates incompetence. Finally, the success of collaboration depends on the nature of the task and what the learners think the task is about. Learners who believe that the task is to develop mastery are more likely to engage in meaningful collaboration than those who have been led to believe that the goal of the task was performance (Luckin, 2010).

4 The Learning Graph Model

For the learning experience to automatically adapt to the personal preferences and skills of the learner as well as to their temporal affect state, a learning experience model capable of deciding the learning material (exercise or task) based on the learning goals, the context and the personal characteristics and temporal state of the learner has to be defined and adopted. Then, this learning model (decision mechanism) has to be implemented together with the subcomponents that allow for identifying the affect state, the personal characteristics, the performance and the context.

With respect to the learning experience modelling, a novel framework is presented in Tsastou, Vretos, and Daras (2017). It has been developed, comprising of

(a) a graph-based representation of the learning objectives (i.e. what to learn) and (b) a knowledge-based schema of the learning activities (i.e. what to do to learn). The graph-based modelling scheme provides educators with the means and method to define reusable, self-sustained and interoperable learning objectives, discretised into smaller learning goals, which represent competences, skills or knowledge that they aim for their learners to acquire. Goals are interconnected in directed learning graphs, with differences in the degree to which they contribute (edge weights). Complex goals comprise the central-most nodes, and atomic goals comprise leaf nodes that contribute to one or more complex goals. These atoms are competencies that cannot be further reduced to more primitive notions.

Generic learning activities are attached to the atomic goals, while different materializations for each activity can be defined based on contextual conditions (device used, etc.). A learning actions ontology has been engineered and presented in the same work, based on educators' and psychologists' feedback, to represent under a holistic schema such abstract activities, but also parameters that affect their materialization in the real world, such as the type of learner, the types of devices used during a learning session, the types of digital content, etc.

Based on this model, personalization and adaptation mechanisms can be summarized as follows in our work: Firstly, the personalization method allows the proposed platform to be initialized in order to maximize the knowledge acquisition of the learners. To that end, performance registered in previous interactions with the learning platform is utilized as the main parameter to establish the appropriate learning content to be deployed along with context information. "Context information" describes whether the learner is in a classroom or at home or on a train, the device available at each environment to select the appropriate learning material to deliver for interacting with and other similar parameters. This process enables the selection of the learning content (and the level of difficulty associated with it) to be used as the first interaction with the learning platform. As a second step, MaTHiSiS focuses its effort on the achievement of optimal affective state of the learners in order to maximize the knowledge acquisition. To that end, the affective state inferred by the platform (through sensorial components (SC) information as well as interaction parameters, e.g. score, time needed to accomplish a task) is utilized. By applying different methods, the values of the affective state, represented by using the theory of flow model, are taken into account for the proper update of the corresponding competences. This update occurs several times during a regular learning experience, adapting the content of the platform (in terms of level of difficulty) according to the affective state registered in real time.

For example, the learning graph may consist of a single learning goal, namely, "understanding numbers", which can be achieved through three distinct learning atoms: "counting", "association of numbers to quantities" and "distinguish greater than from less than", with different participation to the central goal and with "association of number to quantities" bearing the highest importance to the achievement of the goal. This means that mustering this atom will weigh more heavily towards the achievement of the ultimate objective, i.e. understanding numbers, than the achievement of counting, which will fulfil its purpose to this goal in a more

suboptimal achievement state. Each skill denoted through a smart learning atom can be trained by one or more learning actions. The adaptation process will always seek to train the atom with the lowest achievement score out of all the atoms in the graph. For instance, considering the smart learning atom “distinguish greater than from less than” having the lowest weight out of all three in the example above, the system will proceed to train this skill in the next iteration of the learning process, by actuating one of the learning actions attached to it. In this case, “distinguish greater than from less than” can be achieved through a single activity, i.e. exercising with the generic learning action constituting a game (playing action) where one puts numbers in order. This action can be manifested in many ways and, in the particular example, through two related learning action materializations, each of which can be suitable for execution either through the same or different applications (materials) and through the same or different devices (e.g. smartphones, tablets, robots, interactive whiteboards). The system will proceed to present the appropriate materialization for this learning action, that being the materialization that matches the learner’s context at the moment. Therefore, if the user is training on a mobile device, the system will launch the corresponding mobile app, consisting of a game where the learner is asked to drag a series of numbers into slots, in ascending order. A level of difficulty for the materialization is also considered, depending on the competence level of the learner in the skill that they are training at the moment, discretized in three levels (easy, medium and hard). The lower the current score, the easier the materialization level. In the case of this example, given a weight of, for example, 0.5 for the “distinguish greater than from less than”, the chosen level of difficulty would be medium.

For MaTHiSiS to construct a robust collaboration strategy, a new method of adaptation is followed, to maximize the learning experience. In contrast to the “solo” learning experience, the method must consider not only the profile of both learners involved in the activity such as initial level of knowledge about the current learning activity but also their affective state and the performance from previous interactions. This strategy will adapt the level of difficulty of specific social learning actions to maintain both learners in the proper affective state and improve the learning experience. There are obviously several challenges: Given the lack of social skills in learners with severe learning disabilities and autistic characteristics in this project, true collaboration in the sense used by Kerawalla, Pearce, Yuill, Luckin, and Harris (2008) may not be possible. The ambition may be limited to encouraging any prosocial behaviour. Scaffolding is essential. Following the micro-script approach of Dillenbourg and Hong (2008) is one of the most appropriate because MaTHiSiS provides specific options for collaborative actions.

In summary, the collaborative (synchronous) experience has been implemented as follows, following the pedagogical directives and challenges described above:

1. The learners must clearly perceive that they are collaborating with other peers in order to reach positive objectives.
2. They must be able to help or to be helped by other peers.
3. The amount of help received and/or provided must be quantified.

A prototype implementation of the previously described system that exploits and combines the latest information and communication technologies is illustrated in the following figure (Fig. 2). It consists of two interacting sets of components: (a) a set implemented in user devices which we call platform agents (PA) and (b) another set residing in a cloud infrastructure which we call cloud-based learner space (CLS). The users (tutors, learners, caregivers) interact with the PAs which can be desktop/laptop computers, mobile devices, interactive whiteboards or robots, thus providing a broad application potential of the proposed system and warranting efficient ubiquitous learning across a variety of educational contexts. In any given learning environment, a subset of these PAs is considered to exist. Through the platform agents, the users have access to (a) authoring tools to create new *learning graphs*, *smart learning atoms* and *learning action materializations*, (b) a platform configuration component to define the users and devices that will be involved in each learning experience, (c) a *learning experience* execution environment and of course to (d) a simple user interface for account creation and personal detail insertion.

The CLS is the core framework of the system executing processes for data acquisition and analysis (in the form of specialized learning models and educational rules) for predictive modelling and simulation (i.e. feedback analysis and response). These processes are described declaratively and stored in a process repository which executes educational rules and takes higher-level decisions that are streamed to the platform agents. The CLS consists of (a) the Experience Engine that materializes the learning experience by executing the learning graph and sending the relevant information and learning actions to connected agents and actuators. It is a

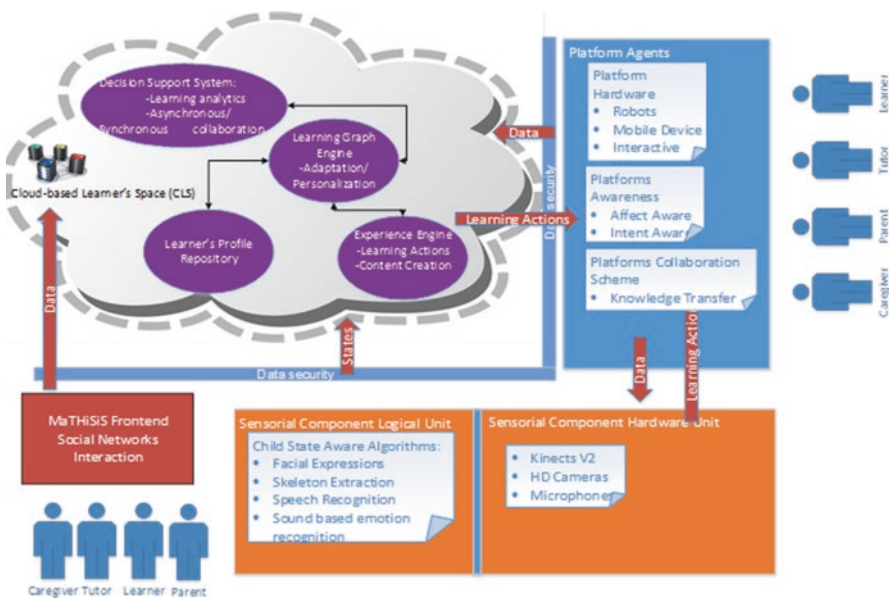


Fig. 2 The architecture of MaTHiSiS with its core technological elements

graph-based interactive storytelling engine that can generate transmedia interactive content, taking multiple forms (e.g. 3D, augmented reality, HTML based), according to the graph-based structure of the scenario. This generated content is then sent to the relevant platform agents that will execute/render it: (b) the Learning Graph Engine that is in charge of adapting the executed learning graph and learner's profile according to (i) her/his behaviour and interactions with the platform agents and (ii) the Decision Support System (DSS) recommendations. The Learning Graph Engine supervises the Experience Engine by adapting the executed learning graph to both the learner's behaviour and profile; and (c) the DSS that provides and collects learning analytics as well as any high-level information to/from the Learning Graph Engine to personalize the learning experience. The DSS controls the synchronous and asynchronous collaboration between different components. The Learner's Profile Repositories are required to store the collected data and the learning graphs for the user profiles. The PA include three major subparts: (1) interface and on-board modules, (2) interunit collaboration modules enabling affect detection and collaborative learning and (3) PA, CLS information and action communication. The so-called SC extracts information from the PA or static sensors. The SC extracts information concerning the learner cognitive and/or physical state to assist the learning analytics module within the CLS.

5 Affect Detection in Real-Life Settings

The sensorial component on the PAs and a subcomponent of the Learning Graph Engine component, in the back end, are the basis of the recognition of the learners' affect states. Their goal is to gather (physical) behavioural cues of the learner and apply machine learning techniques in order to interpret them into comprehensive affective cues that tell the story of the learner's uptake of the learning objective(s). This component can implement state-of-the-art technologies from various fields, spanning from computer vision to artificial intelligence, to extract and represent affect-related features stemming from the learner's face, gaze, body posture, speech and inertia sensors embedded into devices she/he uses. All sensor readings are captured from the user's interaction with devices. If the affect state is shown to tend to boredom, this is signalled to the logic component, and the challenge level is increased. In the case of frustration detection, the challenge is relaxed, so as to keep the learner in the flow state. In the MaTHiSiS system outlined above, a variety of algorithms for affect detection has been implemented and tested per modality. All adopted algorithms utilize machine learning techniques. Thus, appropriate training of the algorithms needs to take place prior to the normal operation of the system. Therefore, we opted for collecting data in the framework of our activities in schools engaging students without and with disabilities. In such cases, the teachers were asked to annotate the captured data with the affect state they believed that the student experienced. At the following, we shall refer to students without disabilities as "mainstream" students. The availability of sensing devices changes per real-life

setting: when the user interacts with a mobile device, it is the gyroscope and inertia sensors that are used to detect the affect state; when the user interacts with an interactive whiteboard or a laptop or a robot, a camera is usually available and assists in affect detection through facial expression or gaze estimation.

The facial expressions are often considered as the strongest indicator of human emotions. They may expose people's feelings and mood state, from simple spontaneous emotions like happiness and disgust to time-dependent affective expressions states like anxiety, boredom and engagement during a current task and/or a situation. This allows the person's interaction counterpart to understand their affective state and adjust their behaviour according to the person's underlying feelings. Facial images are one of the data cues that will be captured through the sensorial component by means of different types of cameras across devices. Due to its high impact, facial images will play a central role along with other data channels to understand learner's affective states.

For the extraction of facial expressions, a graph-based method (D4.2 MaTHiSiS, 2017) has been adopted. More specifically, the face is represented as a graph, which is formed by points extracted from specific areas. The variation of muscle movements on the face during the expression of different emotions leads to different positions of points on the image and may generate different graphs. The input of the algorithm is an image. Then, facial landmarks are detected using the Supervised Descent Method (Xiong & De la Torre, 2013). For instance, such landmarks may be the nose, the eyes, the brows, the mouth, etc. These points are tracked, so that the movement of the facial muscles is followed over time. Assuming that all landmarks are connected, they may be considered as a graph. We then make the hypothesis that the density of the graph differs in each facial expression. More specifically, we use spectral graph analysis, through which a feature vector is extracted. This vector depicts areas of density in the graph by using the graph's Laplacian matrix and solving the eigendecomposition problem for the eigenvectors corresponding to the first and second greatest eigenvalues which capture information regarding different density areas of the initial graph. Such areas in the specific problem are those of the eyes, mouth and nose.

More specifically, the Laplacian matrix L of a graph G is defined as

$$L = D - A, \quad (1)$$

with D denoting the degree matrix and A the adjacency matrix of G . $A(i, j)$ is computed as

$$A(i, j) = 1 - e^{-\frac{(\|x_i - x_j\|)^d}{d}}, \quad (2)$$

where $\|\bullet\|$ denotes the Euclidean distance, x_i, x_j any two given landmark points and d a constant depicting the variance of the overall distance between the facial landmarks. In order to normalize between different image scales and sizes (i.e. for

Table 1 Experimental results of facial analysis

Emotion	Accuracy (%)
Anger	100.00
Disgust	86.37
Fear	60.00
Happiness	100.00
Sadness	75.00
Surprise	100.00

recognition “in the wild”), the symmetric Laplacian matrix is adopted as it is considered to be a more robust option:

$$L^{\text{sym}} = D^{-1/2} L D^{-1/2} \quad (3)$$

Then, its eigendecomposition follows:

$$L^{\text{sym}} v_i = \lambda_i v_i \quad (4)$$

For the classification, support vector machines (SVM) are used. The initial evaluation of the algorithm is done using images from the well-known public available Cohn-Kanade (CK) database (Lucey et al., 2010) leading to very satisfying results. Although this dataset involves expressions of the six basic Ekmanian emotions (Ekman & Friesen, 1978) which are, namely, anger, disgust, fear, happiness, sadness and surprise, a correlation of the aforementioned emotions with affective states was retrieved in Russell’s Core Affect Framework (Baker, D’Mello, Rodrigo, & Graesser, 2010). A direct mapping of the spontaneous emotions to affect states conveys this correlation. Using this mapping, sadness corresponds to boredom, happiness to engagement and surprise and anger and fear to frustration. The performance of this algorithm using the CK dataset to predict affective states reached a classification score that rounds up close to 100% accuracy. Results per emotion are depicted in Table 1.

6 Example Application in Real-Life Use Cases

The approach presented above was tested in real-life cases across Europe. In this section we present the case where the approach was applied to a high-school class and a course of computer science where the students were challenged to learn to use Publisher software. In this case a diverse body of students with a range of cognitive abilities and challenges was addressed. Inclusive mainstream education requires teachers to be competent in addressing particular challenges that some students might face and, at the same time, encourages the growth of already well-performing

students. However, of course, some children are disrupted and can discharge this discontent with uneducated attitudes. Some of them are involved in other cultural or artistic activities like playing music, drawing, etc. and can show great aptitude to subjects such as art design and theatre which allow them to express their feelings. Through this, we realize that in order for them to flourish in their experiences, they must not be ignored but valued in order to meet their full potential. The main issue is they often lack a stable and continuous relation with their parents who are usually busy at work and miss an everyday reference. For this reason, they can feel that it is difficult to interact with their peers or adults, often hiding themselves behind video games or smartphones.

The challenge in this case is to recognize if their learning abilities are improving or if it is time to consider a new method. As these technologies are familiar to the 3–14-year-old age group, they are drawn to them. However, there is also the risk of boredom if the system does not compare well to the games with which they are familiar or if the games are not fast or engaging enough compared to familiar apps. Another purpose addressed in the trials was to make the children collaborate with special needs children to achieve the learning goal by using the same, or similar, learning materials and playing at the same time or collaborating with their peers.

In this scenario, it is the role of parent or caregiver to connect to the platform and start a learning experience for the learner, to select complementary resources from the provided list of resources and finally (optionally) to inspect the visualized performance of the learner. Two different types of learners are supported by the platform: (a) the supervised learner who will use the platform under supervision either because they will use the platform within the school educational path or they have special learning needs or they are minors without special needs and (b) independent learner for those who are advanced learners even when they use the platform within the school or educational path.

Once in action (e.g. in classroom), the tutor selects the graph (associated with a specific learning goal) and also defines the learners in the classroom and the devices each of them will use. The system automatically selects the learning action materialization that will be offered to each learner and adapts its difficulty level in real time depending on the affect state detected. Students in the same classroom may exercise with different learning action materializations. An individual learner may act both as a tutor (selecting the learning goal and the device they will interact with) and as a learner (interacting with the learning action materializations). Caregivers can assist the people they care for by accessing the system through any device available and prompting them to interact with the learning materials available for them. At school, two laptops with webcams and an interactive (web-enabled) whiteboard were available, all centrally maintained. Students were learning to use Publisher. Learning graphs were created prior to the lesson for the quiz section of each lesson. Ethics permission was gained from each student's parents prior to the lessons. One of the learning goals was "know about digital copyright", the Smart Learning Atom in the learning graph terminology was "digital copyright", and the "learning action" was "facts about digital copyright". The different learning materials that were prepared for the trials included three sets of multiple choice questions (with each set

corresponding to different difficulty levels) and three sets of single-question quiz. For the students that interacted with the learning materials either through the laptop or the interactive whiteboard, the performance and the affect state were monitored and used to change the difficulty level whenever boredom or frustration was detected. When the students are at home, they can continue the learning experience through their tablet assuming a suitable learning material is available in the system. In any case, the system will decide which learning material and difficulty level to provide to the learner based on the personal competence registered in the system.

After interviews with the teachers (D8.8 MaTHiSiS, 2017), the overall approach and solution were found promising, even though the tools to build the learning materials were not ready and they had to deliver the learning content to the technical team to produce them. The vision is for the system to support blended, adaptive and collaborative learning.

7 Conclusions

Pedagogy can become significantly smarter exploiting the technological evolution in multiple aspects of different values to the different user roles. It enables learning ubiquity in the sense that it can happen at school/university, at home or even on a train due to the multiplicity of agents that can be used for the learning material to reach us which expands from book to smartphones, tablets, robots, interactive whiteboards and any Internet-connected device. It even enables the creation of experiences through virtual or mixed reality to increase learning efficiency, so long as pedagogists advise developers on the specific design specifications for the augmented reality/virtual reality applications. It enables easy and fast development (using computer-based tools for easy development of materials from presentation to quizzes and games) and reuse of learning materials through learning management systems. It supports fast feedback acquisitions both performance and affect related based on data analytics components. It enables fast and easy learning experience personalization (taking into account the learner profile and the material personalization rules defined by the tutors) and adaptation to the real-time context (e.g. availability of devices) and affect status of the learner (employing sensors and artificial intelligence logic). For society at large to enjoy all these benefits, scientists and pedagogy and technology experts have to work closely together to establish mutual understanding and codesign learning tools whether they be systems, materials or applications.

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