Managing Affective-learning THrough Intelligent atoms and Smart InteractionS

D6.1 Adaptation and Personalization principles based on MaTHiSiS findings

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Abstract:	The main objective of this deliverable is to describe the theoretical background of the approach, which the adaptation and personalization mechanisms within the MaTHiSiS ecosystem will adopt. This document describes the mechanism for establishing correspondence between learner behaviour, tracked during the learning experience, and competence over learned concepts (SLAs), with regard to maintain the learner in an optimal affect state, thereby maximising the rate of learning. A theoretical framework for correlating affective and cognitive learner states to SLA competence weights is devised, in order to support the adaptation mechanisms within MaTHiSiS. It is further enhanced taking into account learning styles and parameters encapsulated in the learner's educational material consumption history and learning progress, in order to provide the theoretical foundation for long-term personalisation. Acknowledging the role of collaborative learning and advantages of social flow, the MaTHiSiS

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	platform also caters for adaptation in multi-learner scenarios.
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List of Acronyms

Abbreviation / acronym	Description
ASC	Autistic Spectrum Case
ASD	Autistic Spectrum Disorder
CGDLC	Career Guidance Distance Learning Case
CERTH	Centre For Research and Technology Hellas
DoA	Description of the Action
DXT	DIGINEXT
HCI	Human Computer Interaction
ID	Intellectual Disability
ITC	Industrial Training Case
IWB	Interactive White Board
LA	Learning Action
LAM	Learning Action Materialisation
LG	Learning Graph
LM	Learning Material
MEC	Mainstream Education Case
NTU	Nottingham Trent University
PA	Platform Agent
PMLDC	Profound and Multiple Learning Disabilities Case
SEN	Special Education Needs
SLA	Smart Learning Atom
VET	Vocational Education and Training
ZPD	Zone of Proximal Development
ZPF	Zones of Proximal Flow

Table 1: Definitions, Acronyms and Abbreviations

Project Description

The MaTHiSiS learning vision is to provide a novel advanced digital ecosystem for vocational training, and special needs and mainstream education for individuals with an intellectual disability (ID), autism and neuro-typical learners in school-based and adult education learning contexts. This ecosystem consists of an integrated platform, along with a set of re-usable learning components with capabilities for: i) adaptive learning, ii) automatic feedback, iii) automatic assessment of learners' progress and behavioural state, iv) affective learning, and v) game-based learning.

In addition to a learning ecosystem capable of responding to a learner's affective state, the MaTHiSiS project will introduce a novel approach to structuring the Learning Objectives for each learner: Learning Graphs. The building materials of these graphs are drawn from a set of Smart Learning Atoms (SLAs) and a set of specific Learning Objectives that will constitute the vertices of these graphs, while relations between SLAs and Learning Objectives constitute the edges of the graphs. SLAs are representations of atomic and complete pieces of knowledge, skills and competences that can be learned and assessed in a single iteration. More than one SLA, working together on the same graph, will enable individuals to reach their learning and training goals. Learning Objectives and SLAs will be scoped in collaboration with learners themselves, teachers and trainers in formal and non-formal education contexts (general education, vocational training, lifelong training and specific skills learning).

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Executive Summary

The MaTHiSiS learning vision is to provide an engaging learning environment in which learners with diverse needs and varying levels of ability are supported with assisted learning, targeted to the learners' personal and situational needs. The environment consists of an integrated platform, along with a set of re-usable learning components and active technological agents that facilitate the actuation of the learning experience. This integrated system is capable of detecting the affect state of the user during the learning process, which is used to adjust the system response parameters in real-time, as well as offline, in order to optimize and personalize the learning experience.

This document describes the theoretical pedagogical and psychological background and the mechanism for establishing targeted system responses, so that the learner is maintained in an optimal affect state during the learning process, thereby maximizing the rate of learning. In addition, the background for establishing the mechanism for long-term evaluation of the learners' responses and progress during the learning experience is presented in this document.

Acknowledging the role of collaborative learning and advantages of social flow, MaTHiSiS reaches beyond catering for individual learners. Through extension of the devised control mechanism, the different long-term and real-time behavioural responses from separate learners are combined to allow for learners of different abilities to work in the same learning space. Such mechanisms will serve as reference for the synchronous collaboration of platform agents. In addition, learners' responses when working with different platform agents will be examined, in order to support the asynchronous collaboration of platform agents aiming at informing the diffusion of the learning process across platform agents, as well as the seamless introduction of new platform agents into the learning process.

1. Introduction

The main objective of this deliverable is to describe the approach taken for the adaptation and personalization mechanism within MaTHiSiS in fulfilment of Task 6.1. The background developed is based on the user requirements drawn in WP2 and technical requirements imposed by Tasks 6.2, 6.3 and 6.4 (individual adaptation and personalisation, synchronous and asynchronous collaboration) and Task 3.3, with respect to the outputs and capacities of the affect recognition tools developed in WP4.

This document examines prior pedagogical and psychological literature, to establish the theoretical background for maximising the efficiency of a technology-assisted educational platform like MaTHiSiS, that aims to tailor education to learners' needs and learning situation. D6.1 defines the strategy for personalisation and adaptation that will map learner interactions (including response to learning activity and time devoted on activity, to be further established in Tasks 4.2 and 4.3) and affective learner response to performed activities, for each iteration of the learning process.

Personalisation in MaTHiSiS refers to the long-term study of the learners' behavioural patterns, in order to adapt the learning experience to the individual learner's needs, before each iteration of the learning process. These patterns take into account implicit affect expression and performance, while at the same time learning styles, preferences and particularities explicitly provided in the learners' profiles are considered.

Adaptation on the other hand, in the context of MaTHiSiS, aims to respond to the moment to moment oscillations in the learners' reception of the learning process, while that is taking place. Its goal is to adapt the system's response in a way that each learner will maintain their engagement to the learning process and therefore maximise skill (knowledge, competence) uptake.

A further objective of MaTHiSiS is to support Collaboration (Tasks 6.3 and 6.4). Synchronous collaboration amongst Platform Agents (PAs) aims to facilitate collaborative learning and Asynchronous collaboration seeks to facilitate cooperation of Platform Agents and smooth integration of new PAs through knowledge transfer. In order to support collaborative learning, all collaborating learners' individual learning statuses taking into account, such that an efficient learning progress is maintained for all involved participants. The principles outlined in this document are therefore extended to cater for collaboration within Task 6.3.

This document is organised as follows: Section 2 will provide an overview of affect states and the pedagogical and psychological implications about them and as a subsequence will present the theoretical background chosen within WP6 in order to support the MaTHiSiS adaptation and personalisation processes. Section 3 will describe how this background will be practically employed within the personalisation and adaptation mechanisms. Section 4 will include the description of the collaborative approaches both for synchronous and for asynchronous collaboration. A conclusion is presented in Section 5.

2. Affective states of learning

An affect state is defined as a "neurophysiological state consciously accessible as a simple primitive non-reflective feeling most evident in mood and emotion but always available to consciousness" [1]. Affect states might include, among others, tension and relaxation, pleasure and displeasure, etc. The main principle is that a person is constantly in an affect state, the intensity and nature of which changes in different timeframes, according to the person's response to stimuli (or the lack thereof) [1].

Learners experience different affective states during the learning process while trying to learn, i.e. specific levels of knowledge, skill, and/or competencies. These activities are organised, in the context of MaTHiSiS, as learning components in Learning Graphs (LGs, Deliverable 3.3 *The MaTHiSiS Learning Graphs* [2]); learning goals and Smart Learning Atoms (SLAs cf. Deliverables 3.1 *The MaTHiSiS Smart Learning Atoms* [3]). Understanding and learning such components is associated with an increase in positive emotions, as well as a decrease in negative emotions like boredom. This perception in turn has a direct influence on their affect state (denoted as 'mood' in the Figure 1 illustration). Positive moods are thought to predict approach goal endorsement while negative moods predict avoidance goal endorsement [4]. The relation between learning components and affect might not be a unidirectional but a reciprocal one as proposed in Linnenbrink and Pintrich's bidirectional model [4].

More specifically, in 2002, Linnenbrink and Pintrich described a model of affect in which goal achievement (i.e. mastering specific learning components) is reciprocally related to the learner's emotional state [4]. In this model (illustrated in Figure 1) the learners' personal goals are highly influenced by their perception of the learning activity challenge.

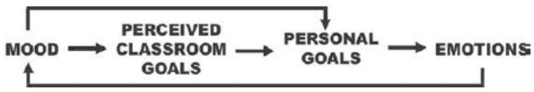

Figure 1: Linnenbrink and Pintrich's asymmetrical bidirectional model of achievement goals and affect

This relationship has also been described in more detail in Csikszentmihalyi's Theory of Flow [5], where learner skill and their perception of the task challenge can let them to exhibit a variety of affect states, presented in Figure 2. However, it has been argued that not all emotions are relevant to learning process in identifying optimal learning experience and moment where the learner requires scaffolding[1]. Sidney D'Mello and Rosalind Picard conducted a study [6] on the relevance of some affect states to learning and found Frustration, Boredom and Flow to be the most relevant ones to knowledge and other competence (for now on simplified to just 'skill' in the remainder of this document).

[1] instructional scaffolding, i.e. the process where instructional support is given to a learner, tailored to their current learning acquisition needs [6]

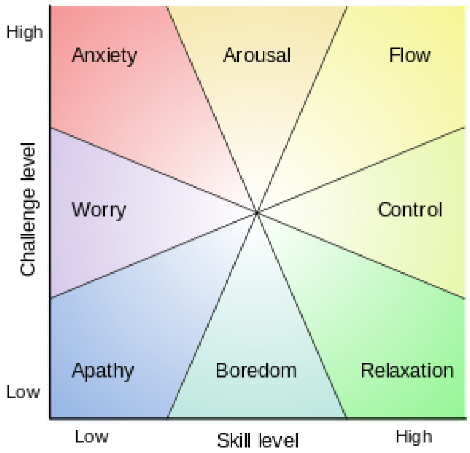

Figure 2: Theory of Flow states

Another helpful explanatory concept is Vygotsky's *Zone of Proximal Development* which he first developed in 1978, to distinguish between what learners can learn independently and what learning they can achieve with assisted learning (instructional scaffolding) from a tutor or a more knowledgeable peer [7]. Vygotsky investigated the advancement of cognitive understanding by becoming interested in the process, and coined the term 'Zone of Proximal Development' (ZPD).

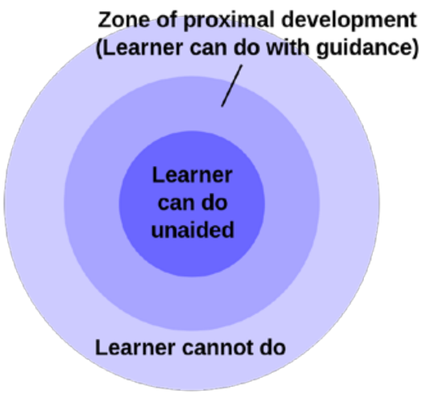

Figure 3: The Zone of Proximal Development

Only later, in 2013, was that a study [8] combined learner skill, independent learning limit and scaffolding in the 'Zones of Proximal Flow' (ZPF) state change diagram. Critically, this work provided the first state change diagram to reference both Vygotsky's ZPD and the affect states from Csikszentmihalyi's Theory of Flow to embrace learning with the aid of peers/supervisors, to apply also to independent learning, which is an important aspect of technology-assisted learning. A diagram of the ZPF states and relations with user skill and task challenge can be seen in Figure 4. The learner's skill level is displayed as the X-Axis and the activity challenge is displayed as the Y- Axis (with values ranging from too easy to too difficult). Unlike Csikszentmihalyi's flow diagram, a single ZPF graph can be used to track the learner's uptake of learning components during a learning activity.

Learning activities in MaTHiSiS comprise of interaction with specific Learning Materials (LMs), which materialise a generic Learning Action (LA) (cf. Deliverable 3.5 *Experience*

Engine [9] for a more detailed definition of LMs and LAs). For the initial design of the MaTHiSiS methodology, the 'challenge' of an activity, as depicted in the diagram of Figure 4, will consist of the difficulty (levels) that a LM has been designed to have, by construction. In later stages of development, the correlation of the LM difficulty level and the response time that a learner has in their interaction with specific LM tasks (e.g. specific achievements completion time, time taken to answer a question/complete a task, overall LM completion time, etc.) will be examined as will the task challenge. This way, the proposed methodology will apply on the relative challenge, with regard to learner perception, as proposed by Linnenbrink and Pintrich [4] (cf. Figure 1).

In MaTHiSIS, learner's skill levels are represented as competence weights attributed to each SLA that a learner is taking on to learn or train at a given moment of the activity – whether that would be during an iteration of the learning process or before/after such an iteration starts/finishes. In this way, the ZPF diagram can represent any permutations of level of skill or task difficulty.

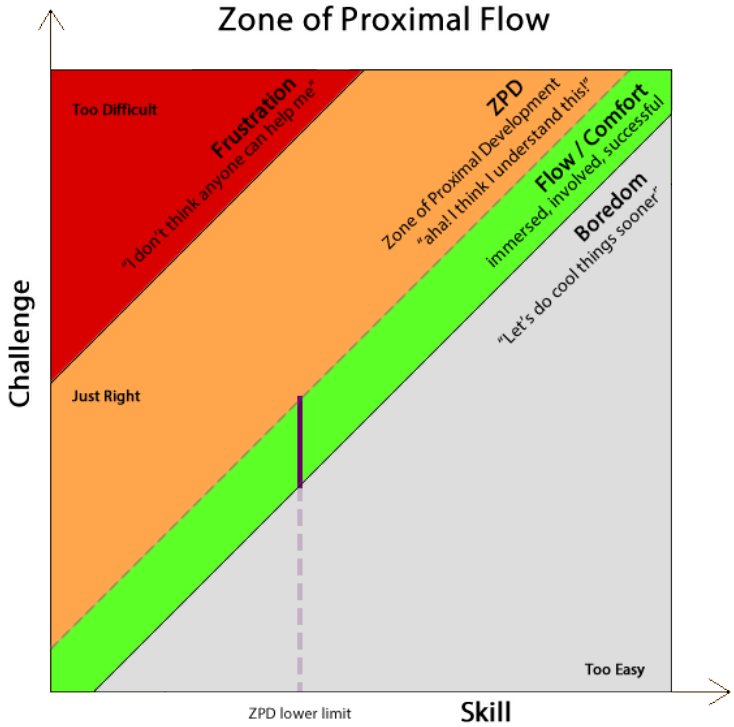

Figure 4: State diagram from the Zone of Proximal Flow theory

2.1 Zones of Proximal Flow states and their relationship with skill acquisition and engagement retention

The Zones of Proximal Flow (ZPF) graph depicted in Figure 4 combine two pedagogical concepts, namely ZPD and Flow, which are represented as learning challenge and skill, to arrive at a strategy for keeping students engaged in learning activities and at the same time maximise the effect of the learning process. Closely related to the idea of engagement is the notion of Flow: this describes the state where the learner is in a completely motivated and engaged state, and when their current skills allow them to easily manage the challenges they are facing during a learning experience.

The idea of Zones of Proximal Flow is an integration of the concept of Flow with Vygotsky's Zone of Proximal Development (the difference between what a learner can do with and without external help) and explains the importance of matching a learner's current level of skill with an appropriate level of challenge. The message here for learning process facilitators (tutors, trainers, an education-targeted decision support system) is that at any given stage of learning the learner would be comfortable (in a state of Flow) performing some tasks unaided. However, in order to progress to tasks of increasing complexity, and subsequently enhance skill or learn new skills, the facilitator has to assist the learner by scaffolding with guidance or demonstration. In this way, the learner then operates within their Zone of Proximal Development. Eventually, these activities will become those that the learners can comfortably perform unaided and thus once again return to the state of Flow.

2.1.1 Frustration

According to ZPD theory, Frustration is where the learner cannot achieve new learning even with assistance. Studies have found that actors who perceive that they lack the skills to take on effectively the challenges presented by the activity in which they are participating experience frustration [10]. Simply if a learner feels incompetent in a given situation, he or she will tend not to be motivated [10]. This is a negative experience and its gravity pulls the learner further into frustration, in a deteriorating cycle that hampers the learning process. In this state, the learner is exposed to a hopeless feeling, their emotional state could be represented with this statement "I do not think anyone can help me".

2.1.2 Zone of Proximal Development

The ZPD refers to 'the state of arousal where the learner can perform an action or skill provided the aid of skilled or knowledgeable tutor or in collaboration with more capable peers' [6]. While in this zone, the student with the assistance of the learning process facilitator (e.g. the tutor or the system in technology-assisted learning) acquires higher skill and is encouraged to learn and mentally develop [7], [11]–[13]. In this Zone the level of difficulty/challenge provides the optimal arousal and engaging experience for the learner. This consists of an individual's learning zone, i.e. the state where the most engaging learning experiences for the learner can happen, where optimal and deep learning opportunities manifest themselves.

According to [14] "deep learning is a committed approach to learning. It is a process of constructing and interpreting new knowledge in light of prior cognitive structures and experiences, which can be applied in new, unfamiliar contexts". Deep learning results in better quality learning and profound understanding. The idea behind deep learning is that neural connections are generated. If engagement allows a higher number of learning opportunities, then the likelihood that enduring neural changes are formed is higher and thus learning is likely to be sustained rather than transient.

2.1.3 Flow

Csikszentmihalyi first described flow in 1997 [1] as the state where the learners are fully immersed, feeling involved and successful. Flow is a delicate state where the skill level and task challenge levels are balanced. This state represents the learner state where the learner is functioning within their independent capacity, i.e. where the learners find themselves in their comfort zone, both in terms of the learning challenge or learning styles. Flow is also the state where new learning materializes as a new skill in the mind of the learner, which provides the learner an opportunity for reinforcement learning, that carries a successful emotional feeling.

Skill advancement in flow however is limited by the learner's lower limit of ZPD (the maximum a learner can achieve independently). Therefore, in order for the learner to achieve new learning outside their independent capacity, the learner must eventually leave flow and be lead to ZPD, to pursue new learning opportunities (i.e. acquire a new skill or to complete competence of partially acquired skill).

This balance is intrinsically fragile. If challenges begin to exceed skills, one first becomes vigilant (i.e. in a state of ZPD) and then anxious (i.e. in a state of frustration). If skills begin to exceed challenges, one first relaxes and then becomes bored. Shifts in subjective state provide feedback about the changing relationship to the environment. Experiencing anxiety or boredom presses a person to adjust his or her level of skill and/ or challenge in order to escape the aversive state and re-enter flow.

While Flow has most often been used to describe 'in the moment' states of an individual, it has been examined in the context of both short and long timescales. Staying in a Flow state is contingent on continuing motivation to prolong the activity underway, which is determined by assessing the individual–environment interaction occurring at a given moment [8]. Flow is a pleasurable state, people desire to repeat experiences that produce it, leading to growth over the long term, both in skill and in the level of challenge to be faced.

Note that either skill or challenge increases can take the lead role at any given point in this progression, with the other factor subsequently rising to complement it. In formal learning environments, it has been found that active learning promotes short-term flow and that flow experiences predict greater persistence and achievement in the associated activity over the long term [15].

The conditions of flow include:

- Perceived challenges neither above or underutilising existing skills;
- A feeling that the learner is engaging challenges appropriate to their capacities;
- Transparent proximal goals and immediate feedback about learner progress;

Under these conditions, the learner enters a subjective state with the following characteristics:

- Focused concentration the activity at the current moment at hand;
- The unification of action and awareness;

- Loss of reflective self-consciousness (i.e., loss of awareness of oneself as a social actor);
- A sense that one can control one's actions; that is, a sense that one can in principle deal with the situation because one knows how to respond to whatever happens next;
- Distortion of temporal experience (typically, a sense that time has passed faster than normal);
- Experiencing the activity as intrinsically rewarding, such that often the end goal is just an excuse for the process.

2.1.4 Boredom

Boredom is the state where the learner is not challenged sufficiently. This state can manifest through the addition of a dry skill base through lecture style teaching, or by providing interactive activities that do not challenge the learner outside what they have already learned. Boredom is a negative feeling and its gravity pulls the learner further into this state, leading to learner disengagement and stifling learning progress. In this state the learner's emotional state could be represented with the statement: "let's do interesting things sooner".

In boredom, the low level of challenge relative to skills allows attention to drift. Particularly in contexts of extrinsic motivation, attention shifts to the self and its shortcomings, creating a self-consciousness that impedes engagement of the challenges. Goetz and Hall review development of learners' boredom, and call it an emotion that is frequently experienced by students and can undermine their learning and performance [16].

3. Individual adaptation and personalisation principles

As aforementioned, personalization in MaTHiSiS is the study of the long-term response of the learner to the learning experience. Therefore, it is performed before the beginning of each iteration of the learning process. Data related to previous interactions of the learner with the learning platform is used to make an informed decision of the long-term status of skill level, and subsequently the choice of the first learning action to be used in the new iteration. This data is based on the performance history of the learner and takes into account factors such as his/her skill level records, scores obtained during previous sessions, time required to finalize the learning activity, etc. Through the analysis of this information the learning experience will begin with the optimal learning action materialisation, in the optimal level of difficulty, in order to maximise the chance to maintain the learner in the path of proximal flow, and thus maximise skill acquisition.

Once the learning experience has started, the selection and change in the learning content is mainly based on the learner performance analytics and the affect state, trying to guide or maintain the learner on this optimal path. In the MaTHiSiS context, this is called adaptation. Adaptation will initially be manifested at certain critical moments that are defined as a result of the analysis performed by pedagogical experts (i.e. key moments as defined in Deliverable D2.2 *Full scenarios of all use cases* [17]). In these key moments, the learning action materialisation, whether that will be the selection of the learning material itself or its difficulty level, will potentially be modified in order to, as in the case of personalisation, maintain the learner in the optimal path and encourage knowledge acquisition.

The use of computer-mediated learning in education is not new. It has been found to improve uptake of abstract conceptualizations and enhance reflective observation [18]. Maintaining learner engagement is important to ensure learning and skill achievement. Therefore, the design of a successful technology-assisted learning platform should automatically consider how to maximise learner engagement and therefore optimise the learning experience and the uptake of knowledge.

A possible approach to ensure learners' engagement is the application of game-based learning. Connelly et al. found in a systematic review of 129 papers [18] that playing serious games impacts across a range of areas including engagement, cognitive ability and, most commonly, knowledge acquisition and content understanding. The MaTHiSiS approach will consider game-based learning approaches (especially in primary and secondary education for MEC, PLMDC and ASC) and will rely on the adaptation and personalisation of the learning experience to maintain learners' engagement and ensure the required levels of skill attainment.

3.1 Maintaining engagement and maximising learning process efficiency

Student engagement (participation in learning) was found to be the most reliable feature for determining successful learning [19], [20]. Without engagement, deep learning is not possible [21]. Effective personalized learning was shown to encourage participation and engagement not only in the classroom but in extra-curricular activities and work related learning in the local community [22]. As the tutor or the technological learning facilitator forms a better understanding of the learners' strengths and challenges, they are in a better position to go through scaffolding objectives, involving choice of skill to train at a given moment and choice of learning activities, while preserving the learners' interest and engagement [23].

According to Carpenter [24] the process of engagement is a journey that connects learners and their environment (including people, ideas, materials and concepts) and enables learning and achievement. Students who are not engaged can become frustrated or bored, which can have a negative effect on achievement and lead to disruption of learning, for the individual learner, as well as for other learners when learning takes place in a collective/collaborative environment like a classroom.

3.1.1 Optimal learner experience reflected through Zone of Proximal Flow state transitions

Guided by the state of affect the MaTHiSiS platform can capitalise on the ZPF theory to create a positive and effective learning experience for the learner. The MaTHiSiS methodology focuses on understanding and defining the level of achievement of one or more pieces of knowledge or skill competence, encapsulated in the SLA concepts, that the learner is taking upon learning at any given point in the learning process. The SLA competence weight (cf. Deliverable 3.1 for more details [3]) is directly related to the skill level in the ZPF theory. Through that correlation, MaTHiSiS can determine the appropriate level of challenge over executed tasks, as defined in Deliverable 3.5 [9], in order to maintain the learner at an optimal condition where both engagement, as well as skill is maximised.

Skill is graded against the maximum skill an expert can achieve in an activity, the ground truth. For example, if the activity is to perform the ballet move 'en pointe', an expert performer (in MaTHiSiS this is the tutor) sets the gold standard to achieve this maximum excellence in performance, this is the highest value on the x-axis in the ZPF graph (Figure 4).

In this way, the graph can be used to plot more than one learner, two ballet students could be plotted on the same ZPF graph - but importantly setting a global not relative ground truth allows the system to influence the user's movements in the graph with only one independent variable, 'challenge'. The ground truth is set against tangible measures that can be tested (by the expert or the indicators the expert sets the system to monitor) in MaTHiSiS this monitoring is achieved through performance analytics and affect state tracking.

The challenge level will be directly mapped to each LM's difficulty levels. Similarly, subsequent platform versions will combine the information from the examination of the affect states with the user performance analytics in order to determine the progress over the current SLA(s) at each given point of the learning experience.

Performance in itself is a multi-dimensional parameter, which depends on the learner's interaction record and their scores in learning materials such as quizzes and serious games, etc. Performance will be established and further solidified in Task 4.3 (Multimodal learning analytics) as learner's performance analytics.

The 'flow' and 'ZPD arousal' learning states are the active learning states of the learner. New skill acquisition and skill uptake maximisation happens in ZPD, while maintaining the learner in the state of flow provides the opportunity for reinforcement learning (as visualized in Figure 5) which can solidify skills acquired during the learning process and enhance the learning experience itself.

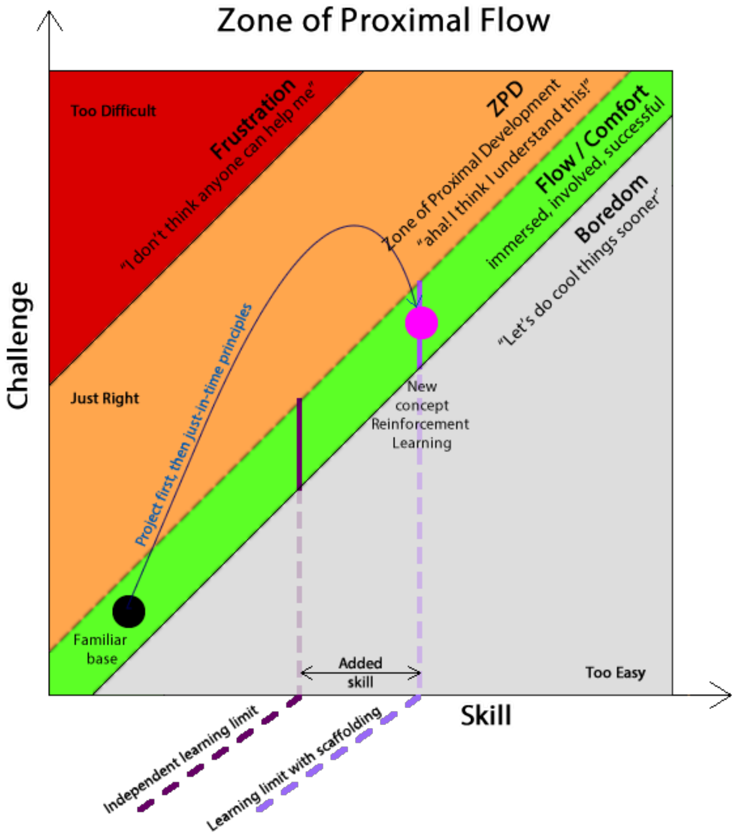

Figure 5: Reinforcement learning in Flow

Although new skill is not acquired in flow, according to the principles presented in Section 2.1.3 Flow, a slow parallel growth over the long term, with the increase of the level of challenge, introducers an increase in learner skill. This is however limited to the to the lower ZPD independent learning limit, and to increase skill further beyond that, the learner must enter the ZPD.

The adaptation processes in MaTHiSiS need to maintain the learner in the optimal path, considering the affect states described in Section 2.1, as portrayed in Figure 6. To this end, the level of challenge must take the learner through arousal and avoid boredom or frustration. While allowing the learner to remain in the state of flow to enable reinforcement of acquired knowledge (reinforcement learning). However, the 'familiar base' (starting concept) should be challenged for specific learners with disability to re-evaluate the subsistence of previously established learning outcomes.

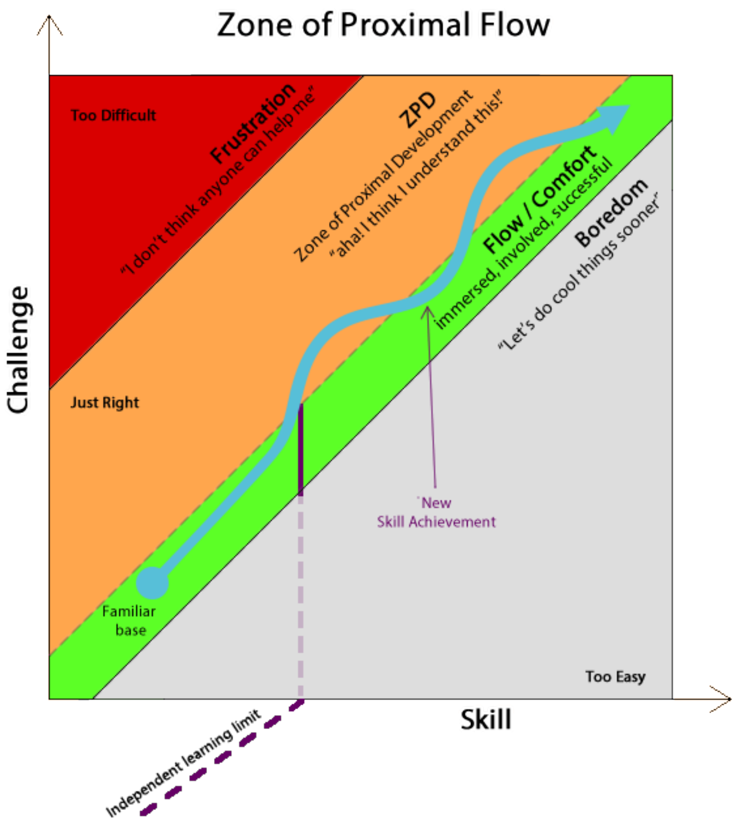

Figure 6: Optimal learning experience loop

Another reason to proportionally increase challenge level while the user is the state of flow, is the fact that if challenge of the performed task remains the same while a skill is reinforced, the learner may get bored. Boredom is a negative feeling and its gravity pulls the learner further into the grey area illustrated in Figure 6. This has a strong possibility of leading to learner disengagement. Nonetheless, if the learner drifts from the optimal path towards boredom, parameterisation of challenge levels (difficulty of LM in MaTHiSiS) is needed in order to pull the learner back to engagement, as depicted in Figure 7.

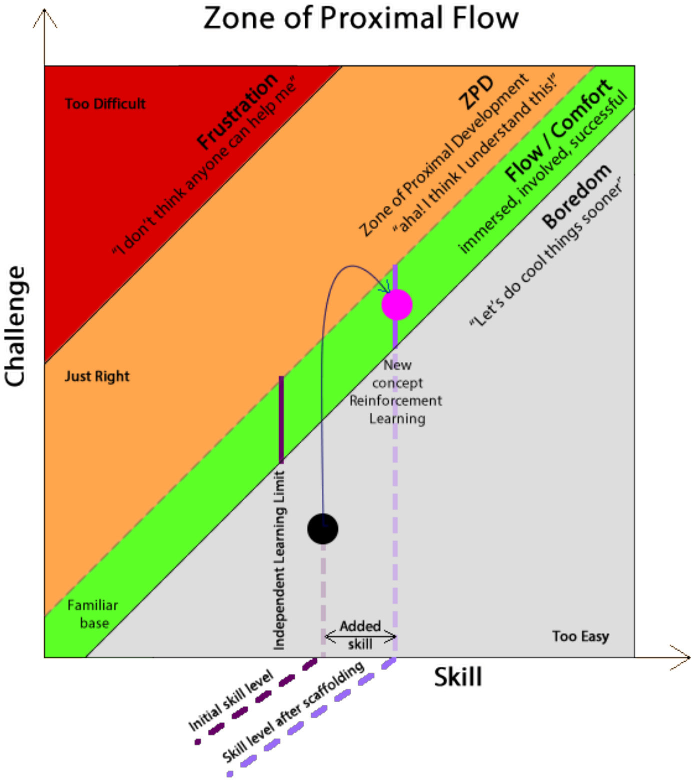

Figure 7: Tracking back to the optimal path from boredom

To this end, continuous efforts to push the learner out of their comfort zone and into the arousal state by challenging them to greater levels of difficulty in undertaken activities will stimulate the learner and stand a better chance to avoid spiralling them into boredom. The peril here is to avoid projecting the learner too far up the arousal state and into frustration (as visualized in the 'current state' of Figure 8). Therefore, again appropriate temporal parameterisation of skill level, and subsequently challenge level, is needed in order to guide the user back to the ZPD zone and on track with the optimal learning path.

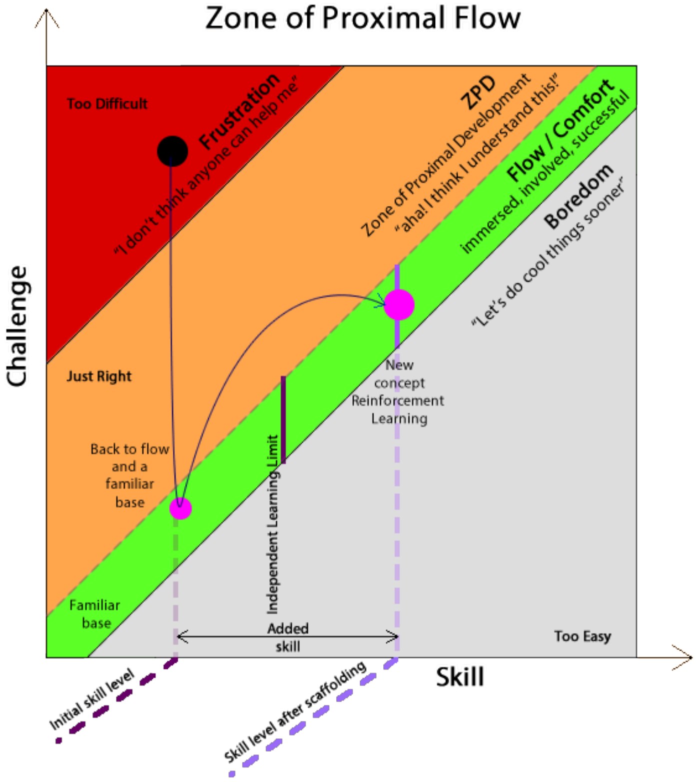

Figure 8: Tracking back to the optimal path from frustration

As personalisation in MaTHiSiS is performed before the beginning of the session, it won't use the learner's affective state directly. At the first iteration of the learning process for a new learner, it will consider explicit information about the learner (cf. Section 3.2), which are stored in the user profile and have been declared when the new learner information was inserted into the system. After this initialisation, personalisation principles to be developed in a future deliverable (D6.2, D6.3 MaTHiSiS Learning Graph Engine), will take into account the learner's history in skill level, learner performance and learning material challenge during the learner's usage of the MaTHiSiS platform to determine the initialization skill level and challenge of the learning material at the start of the iteration of the learning process.

Personalisation will use the aforementioned parameters in the learners' history in order to establish the initial configuration of the learning content to try to figure out the right skill/challenge balance so that the learning experience in the desirable learning state (namely Flow or ZPD). For that reason, the personalization mechanism will initialise the learning experience at the last established mastered challenge level to avoid unnecessary repetition.

3.2 Personal learning experience parameters

There is a range of different learning styles that support the facilitation of personalization in MaTHiSiS. Teachers across disciplines and countries can adapt a wide range of learning approaches they already utilise in the MaTHiSiS solution in order to facilitate neutrality in learning method and styles. These learning styles will be activated depending on the curriculum content, discipline, age and specific learning needs of individual students. The VARK learning styles [25] are particularly suited for multi-media learning platforms, as it addresses the use of audio, text, video and tangible objects in a learning environment to offer the student a choice of the most accessible formats.

Another use case for the VARK learning style is the Autism Spectrum Disorder case. People with autism spectrum conditions in particular tend to become specialists in just one sensory modality, more than non-autistic people, due to impairment in the cognitive control that is necessary to rapidly shift amongst and integrate multiple perceptual channels. This is especially true in the case of the severe end of the autism spectrum, in which cognitive control is most impaired. Soma Mukhopadhyay refers to this specialized input modality as the 'open learning channel' [26]. For most people with autism, the visual style is a common preference, however for a significant portion, auditory is the style of choice. Many visual learners develop a specifically lexical fascination and a precocious ability for decoding graphemes to phonemes, albeit often without comprehension.

The VARK model is in accordance with the capacities of the MaTHiSiS platform and bears correspondence with the categorisations of types LMs and PAs defined in the Learning Actions Ontology (LAO, cf. Deliverable 3.5 [9]). The principles of this approach can be adopted by the MaTHiSiS, where favourite types of LMs and types of PAs can be declared in the Learners' Profile in order to accommodate each of the learner's needs including VARK learning style preferences.

MaTHiSiS' Experience Engine (EE – cf. Deliverable D3.5 [9]) can take these parameters into account, as personalised facts, before finally deciding on the best Learning Action Materialisation (LAM) choice for each learner at the beginning of the learning process.

4. Adaptation and personalisation in collaborative environments

4.1 Synchronous collaboration

Grasha-Reichmann Learning styles [27] list 'avoidant', 'participant', 'competitive', 'collaborative', 'dependent', 'independent' as collaboration learning styles that can be used to coordinate compatible learning groups or pairs that nurture successful peer-to-peer scaffolding opportunities.

4.1.1 Principles and impact of synchronous collaboration

Research around the use of learning environments to support collaborative learning identifies positive impact on student learning, however Dillenbourg and Schneider [28] identified that depending on the activity the learning environment may need to be regulated by the tutor. Rovai [29] identified that as students work collaboratively they are co-constructing knowledge and supported in becoming independent, self-directed learners.

Collaborative learning provides an opportunity to learn through the eyes of a peer. This learning could happen indirectly through the observation of another learner's achievement or failures or could happen directly through the scaffolding of a more knowledgeable peer. This process happens naturally in any learning environment: a student will watch and learn from other peers' interactions with the learning experience, and not make those mistakes, or improve on the peer's performance.

MaTHiSiS introduces a new dimension of collaboration through mediated learning, which offers the possibility to enhance this collaboration between learners with different learning profiles and levels of skills achievement. In the context of MaTHiSiS, the definition of multi-learner (two learners) scenarios is facilitated through the synchronous collaboration among platform agents allowing to mediate the collaborative learning process. This scenario implies a new student-MaTHiSiS-student relationship (in contrast to the traditional, student-teacher one). This synchronous collaboration among Platform Agents is focused on the strategy "one learner – one PA". This approach also enables the sharing of the learning experience between two learners physically separated.

This collaborative scenario will make it possible for platform agents of heterogeneous nature to exchange information and work together in order to offer a smooth and optimized multi-learner scenario. This kind of scenario will allow learners with different knowledge background and skill levels to work together in the same schema. This approach can provide a beneficial improvement in the engagement of the students, in contrast to the solo experience.

In order to materialise this collaboration strategy, new methods of personalisation and adaptation are needed to maximise the learning experience. In that case, the method must take into account 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 collaborative learning styles. This strategy will adapt the level of difficulty of specific social learning activities to maintain both learners in the proper affective state and improve the learning experience for both. For an example of a multi-learner MaTHiSiS use case, refer to Annex I in Section 7.

The implementation of collaborative learning styles within the MaTHiSiS platform also allows for potential social advantages that will improve the learning experience.

Social anxiety and judgement: Collaborative learning provides a rich experience for learners to learn from example or by demonstration from a more knowledgeable peer. This experience is far more enhanced and more sensory-rich and impactful than mediated collaboration through a learning device. However, peer-to-peer collaboration is a natural process, which occurs spontaneously and incurs social aspects of learning that can negatively arouse people with social anxiety sensitivities.

In the case of autism, the very fact that two learners are involved in a cooperative activity - or at least in simultaneous activities in which context they are aware of and sensitive to each other - says something about the learners. Some people with autism simply are not interested in social stimuli or social interaction, whereas in others - more numerous - the problem is that they are interested but don't know what to do with social stimuli, how to respond in kind or how to respond synchronously 'in the moment'. Therefore, members of the former autistic subpopulation aren't going to be involved in cooperative learning in the first place. For members of the latter subpopulation, the establishment of social reciprocity can be aided by removing the requirement for social synchrony. For example, many people with autism do better socially via a textual medium (e.g. Internet chat) than they do face–to-face, and many people with autism will look at another person through a video camera even when looking at that same person 'live', because face-to-face would evoke too much anxiety for them to bear.

For members of this second, socially motivated subpopulation, the very same motivational techniques that work for non-autistic people work for them too - as long as accommodations are in place to make social interaction possible, for example modifications that remove the requirement of face-to-face synchrony as detailed above. In this context, it is indeed very useful for one learner to pull another less skilled learner out of their comfort zone into a more efficient learning zone. MaTHiSiS will be able to adapt the collaborative scenarios in order to reduce the anxiety of the learners of this use case and provide a more comfortable and effective learning experience.

Obstacles related to physical location of the learners: The collaborative scenarios defined in the context of MaTHiSiS will also implement mechanisms to avoid obstacles related to physical location of the learners.

4.1.2 Personalization and adaptation in multi-learner settings

Initially, the MaTHiSiS platform considers the approach of collaboration between two learners under the strategy of “one learner – one PA”. In cases where the collaboration learning styles of the learners are known, there is an opportunity for MaTHiSiS to facilitate the ZPD zone of proximal learning with a more knowledgeable peer. In this way, MaTHiSiS is making a distinction between the ZPD facilitated by the learning material provided by MATHiSiS and the ZPD opportunity presented by peer-to-peer collaboration, which may exceed the range of the MaTHiSiS ZPD. Some conditions should be met however, and observations need to be made afterwards to consolidate these decisions and learn from them historically.

Consider the scenario where Peer A is more knowledgeable than Peer B, these conditions apply:

1. Peer A should have shown more skill in the learning activity than Peer B;
2. Peer A’s collaboration profile should support that he/she is a learner that is comfortable to share knowledge and scaffold other peers. This however, may happen or it may not happen. This is why follow-up observations and historic data are crucial in making these decisions;
3. Peer B must be in a lower skill level than Peer A.

When these conditions are met, the system can make decisions for both Peer A and Peer B based on the affect state of Peer A, then pause and prompt both learners to discuss among themselves their learning and questions.

Consolidation needs to be made to check if the peer scaffolding has been successful between learners. This should be done by assessing the skill (SLA competence weight) of all learners to see if peer scaffolding has been successful. Similar consolidation is needed when learning evaluation and skill achievement validation takes place in state of flow to access the level of skill achievement success.

Overall, there are four different outcomes of a peer-to-peer collaboration opportunity:

1. Peer A does not scaffold Peer B;
2. Peer B is not receptive of Peer A scaffolding;
3. Peer B given Peer A’s scaffolding does not extend the ZPD range of Peer B;
4. Peer B is scaffolded outside their natural range with MaTHiSiS and the peer-to-peer collaboration opportunity has been successful in extending the natural skill range of Peer B.

Historic knowledge of peer-to-peer collaboration, specifically between known peers in the same learning activity, can provide useful information to support MaTHiSiS decisions in providing collaborative opportunities or not. Have these peers scaffolded each other successfully before? What was the skill achievement outcome of the peers collaborating?

Knowing the collaborative learning style of the peers can inform MaTHiSiS to avoid collaboration if their collaborative learning styles are not compatible. Peer A most likely will not scaffold Peer B if Peer A or Peer B has an avoidant collaboration learning style – this avoids above-mentioned cases 1 and 2. Knowing the skill level can assist MaTHiSiS in avoiding cases where Peer A is more knowledgeable but not knowledgeable enough to scaffold peer B outside their natural ZPD zone – this avoids case 3.

4.2 Asynchronous collaboration

Another important kind of collaboration included in MaTHiSiS project is the asynchronous collaboration. This concept relates to the physical location of the learners, allowing learners the access to the learning platform through different PAs in different locations, and to facilitate the addition of new PAs or learning content using knowledge acquired previously (well-known PAs or LMs). To this end, this section examines the requirements and methodology to achieve smooth knowledge transfer from an existing Learning Action Materialisation (LAMs, focused particularly on PAs and/or LMs) to another. Knowledge transfer aims to organise, create, capture or distribute knowledge so that it will ensure the easy integration of future PAs and LMs to the MaTHiSiS ecosystem.

Asynchronous collaboration includes the following main objectives:

- Different materialisations of a same learning action (LAMs) depending on the available PAs.
- Reusability of knowledge to facilitate emotion recognition using new sensorial components [30].
- Reusability of knowledge to facilitate the introduction of a new Learning Material (LM) or Platform Agent (PA) to the platform.

MaTHiSiS includes the possibility of using different PAs to materialize the same (or different) learning actions. This functionality is very useful to allow “anywhere, anytime” learning and learners can use it, for example, to continue an already started learning experience in another location, using different PAs.

One of the major innovation activities of MaTHiSiS will involve knowledge sharing, allowing the reusability of knowledge to facilitate the addition of new PAs (which might include unknown sensorial capacities) or learning material. Firstly, the knowledge of well-known, sensorial components (SC) will be used - along with a reduced amount of data gathered through a new sensor - to train the method to estimate the affective state using the new sensorial modality. Using transfer learning techniques, an under-sized database could be used to incorporate new modalities into the platform. This method avoids the necessity of gathering large amounts of data, facilitating the addition of new PAs.

Likewise, the knowledge acquired by the use of different LAMs, in combination with related SLAs, will be used to facilitate the incorporation of new LMs within the platform. Using reduced information, related to interactions of similar learners during the use of the new LM, the system will propose a correspondence of materialisation and SLA weight for the new material, in order to alleviate the cold-start problem in an already established learning experience. For that purpose, asynchronous collaboration will identify mappings between materialisation and SLA weights for new LMs.

5. Conclusions

This document presented the main pedagogical approach that will drive the technical implementation of the MaTHiSiS adaptation and personalisation mechanisms in order to optimise the actuation of the learning process and subsequently the uptake of skills within the MaTHiSiS ecosystem.

The main MaTHiSiS components that benefit from the foundation laid in this document will be the individual and collaborative (multi-learner) adaptation and personalisation mechanisms of Task 6.2 and Task 6.3 respectively. In addition, the basis established here significantly impact the practices of the asynchronous collaboration (multi-agent learning experience, Task 6.4) and the Experience Engine (cf. Deliverable D3.5 *Experience Engine* [9]). The Learning Action Materialization Editor will take into account T6.1's results in its design methodology, in order to provide the appropriate Learning Action Materialization construction outline, variables and constraints. The Experience Engine will also take into account T6.1's results in order to design the decision-making algorithm that will select the appropriate Learning Action Materialization for the learner at each iteration of the learning process.

A literature review has been carried out to form the theoretical background for coupling learning to the emotional state of the learner. The Zone of Proximal Development and theory of Flow are combined into the Zone of Proximal Flow is found to be the most relevant pedagogical approach for MaTHiSiS, given the system's requirements and capabilities. This mechanism provides the means of balancing Challenge vs Skill based on the learner state of affect. The relationship between the four Zones of Proximal Flow and skill acquisition is also defined.

Furthermore, the foundation for multi-learner and multi-agent collaboration strategy is laid in this document. In multi-learner environments, smooth and optimised learning experiences will allow for learners with different level of skills to work together in the same learning scenario and environment, through mediated collaboration. Finally, considerations about the seamless transfer of the learning process to different PAs, are outlined in this document, in addition to the transfer of knowledge, such that allows for the easy incorporation of new PAs to the MaTHiSiS ecosystem.

6. References

[1] D. Shernoff, M. Csikszentmihalyi, B. Schneider, and E. Shernoff, “Student engagement in high school classrooms from the perspective of flow theory,” *School Psychology Quarterly*, vol. 18, no. 2. pp. 158–176, 2003.

[2] CERTH (eds.), “D3.3 The MaTHiSiS Learning Graphs M12. Deliverable of the MaTHiSiS project.” 2017.

[3] DIGINEXT (eds.), “D3.1. The MaTHiSiS Smart Learning Atoms M12. Deliverable of the MaTHiSiS project.” 2017.

[4] E. Psy-, *International Handbook of Psychology in Education*. 2010.

[5] M. Csikszentmihalyi, “The Flow of Creativity,” *Creat. Flow Psychol. Discov. Invent.*, pp. 107–126, 1996.

[6] S. D. Mello, R. Picard, and A. Graesser, “Towards An Affect-Sensitive AutoTutor.”

[7] S. Chaiklin, “The zone of proximal development in Vygotsky’s analysis of learning and instruction,” *Vygotsky’s Educ. theory Pract. Cult. Context*, pp. 1–21, 2003.

[8] A. Repenning, “The Zones of Proximal Flow : Guiding Students Through a,” pp. 67–74, 2013.

[9] DIGINEXT (eds.), “D3.5 Experience Engine M12. Deliverable of the MaTHiSiS project.” 2017.

[10] M. Csikszentmihalyi, J. Nakamura, and S. Abuhamdeh, “Flow A General Context,” *Handb. Competence Motiv. (pp. 598-608)*, pp. 598–608, 2005.

[11] J. Radford, P. Bosanquet, R. Webster, and P. Blatchford, “Scaffolding learning for independence: Clarifying teacher and teaching assistant roles for children with special educational needs,” *Learn. Instr.*, vol. 36, pp. 1–10, 2015.

[12] C. Read, “Scaffolding children’s talk and learning,” *Child Psychol. Psychiatry*, pp. 1–18, 2006.

[13] I. Verenikina, “Understanding Scaffolding and the ZPD in Educational Research,” *Development*, p. 8, 2003.

[14] J. Hermida, *Facilitating Deep Learning: Pathways to Success for University and College Teachers*. 2015.

[15] J. Nakamura and M. Csikszentmihalyi, “The Concept of Flow Optimal Experience and Its Role in Development,” *Handb. Posit. Psychol.*, pp. 89–105, 2002.

[16] L. Robertson, *International handbook of emotions in education*, vol. 31, no. 1. 2015.

[17] NTU (eds.), “D.2.2 Full Scenarios for all Use Cases. Deliverable of the MATHISIS project.” 2016.

[18] T. M. Connolly, E. A. Boyle, E. MacArthur, T. Hainey, and J. M. Boyle, “A systematic literature review of empirical evidence on computer games and serious games,” *Comput. Educ.*, vol. 59, no. 2, pp. 661–686, 2012.

[19] R. Iovannone, G. Dunlap, H. Huber, and D. Kincaid, “Effective Educational Practices for Students with Autism Spectrum Disorders.,” *Focus Autism Other Dev. Disabil.*, vol. 18, pp. 150–165, 2003.

[20] B. Carpenter, J. Egerton, B. Cockbill, T. Bloom, J. Fotheringham, H. Rawson, and J. Thistlethwaite, *Engaging Learners with Complex Learning Difficulties and Disabilities: A resource book for teachers and teaching assistants*. Taylor & Francis, 2015.

[21] D. H. Hargreaves, “A new shape for schooling?,” 2006.

[22] J. Sebba, N. Brown, S. Steward, M. Galton, and M. James, “An Investigation of Personalised Learning Approaches Used by Schools,” 2007.

[23] R. Dolan and T. Hall, “Universal Design for Learning: Implications for large-scale assessment,” *IDA Perspect.*, vol. 27, pp. 22–25, 2001.

[24] “Engaging children with complex learning difficulties and disabilities in the Primary Classroom. Barry Carpenter,” no. 2002, 2011.

[25] N. D. Fleming and C. Mills, “Not another inventory, rather a catalyst for reflection,” *To Improv. Acad.*, vol. 11, no. 1, p. 137, 1992.

[26] G. M. Chen, K. J. Yoder, B. L. Ganzel, M. S. Goodwin, and M. K. Belmonte, “Harnessing repetitive behaviours to engage attention and learning in a novel therapy for autism: An exploratory analysis,” *Front. Psychol.*, vol. 3, no. FEB, pp. 1–16, 2012.

[27] J. H. Ford, J. M. Robinson, and M. E. Wise, “Adaptation of the Grasha Riechman Student Learning Style Survey and Teaching Style Inventory to assess individual teaching and learning styles in a quality improvement collaborative,” *BMC Med. Educ.*, vol. 16, no. 1, p. 252, 2016.

[28] P. Dillenbourg, D. K. Schneider, and P. Synteta, “Virtual learning environments,” *3rd Hell. Conf. "Information Commun. Technol. Educ.*, pp. 3–18, 2002.

[29] A. P. Rovai and H. M. Jordan, “Comparative Analysis With Traditional and Fully Online Graduate Courses,” *Int. Rev. Res. Open Distance Learn.*, vol. 5, no. 2, p. 13, 2004.
[30] CERTH (eds.), “MaTHiSiS Sensorial Component M12. Deliverable of the MaTHiSiS project.” 2017.

7. Annex I

7.1 Use Case 3: Mainstream Education

7.1.1 Worked Example (Multi-learner)

7.1.1.1 Stakeholders

Sam and Dave are both 11-year-old boys who are in their first year at secondary school (year 7), having been to a mainstream primary school since they were 4-year-old.
Sam has a high level of cognitive ability and has always been in the top 5% of his class. Dave has a moderate level of cognitive ability and has struggled to stay been in the top 50% of his class.

- Primary Actor - Teacher
- Actor – Sam (student)
- Actor – Dave (student)
- Other actors – Headmaster, Parents

7.1.1.2 Learning Experience Examples

Sam and Dave are working on developing computing skills, knowledge and understanding. They are starting a module that will introduce them to Flowol, a computer control software that they have not used before.
They will be in proximity and working together through the mediation of separate platform agents.
Sam and Dave need to be able to:

- Order cards into correct sequence for pelican crossing (this example);
- Develop a control flowchart solution for a simple problem;
- Identify control flowchart symbols and understand how they are used to break down problems.

7.1.1.2.1 Example 1: Sequencing (sorting)
Order cards into correct sequence for pelican crossing

- PA: PCs
- Learning goal: Programming skills (improvement)
- SLA: Sequencing (sorting)
- LA: Sort cards into logical order

Students each have the same view of the activity - slots for the cards to be sequenced in, an area for Sam's cards, and an area for Dave's cards.
The cards are distributed between the students, and ownership of each card is indicated on the card.
Any card can be moved, but only the owner of a card can place it, if it is not moved by the owner, it will snap back to its starting location.
Card sequence to use (3 levels of complexity):
a) Initiate crossing request
    1.1) Normal status (pedestrian lights: red man, traffic lights: green)

1.2) Press button
2.3) Illuminate WAIT indicator
2.4) Wait until ready to start crossing sequence

b) Stop traffic
3.5) Set traffic lights to amber (for 1 second)
3.6) Set traffic lights to red
4.7) Wait for 2 seconds

c) Cross road
5.8) Set pedestrian lights to green
5.9) Darken WAIT indicator
6.10) Wait for crossing time (for 15 seconds)
6.11) Set pedestrian lights to flashing green man (for 5 seconds)

d) End crossing request
7.12) Set pedestrian lights to red man
8.13) Set traffic lights to red and amber (for 1 second)
8.14) Normal status (pedestrian lights: red, traffic lights: green)

The combined steps could either be represented by a summarised card, or by the card elements being hard-linked together (which would facilitate different learners working at different levels of complexity).

The LA as described will then ideally run 3 times, first at the summary level (summary cards), then at the second level (linked groups of cards) then at the tertiary level (individual cards). Affect state can be accommodated by presenting simpler or more complex combinations as appropriate (possibly even modifying grouping in a single materialisation of an LA).

Learning Experience Flow

1. Teacher sets up the system (target number of cards for each) and starts the LA “Sort cards into logical order” exercise.
2. Cards appear on the screen in random order, shared between Sam and Dave.
3. Students are instructed to drag and drop cards into correct sequence.
4. Students place cards into correct order.
5. Students receive congratulations message on PC.

Termination outcome: cards are presented in correct sequence by Sam and Dave.

Alternative Flow 4A

4A1. Sam and Dave place all cards, but not in the correct sequence.
4A2. PC gives them a prompt.
4A3. Go to 3.

Alternative Flow 4B (Collaboration)

4B1. Dave places a card in the wrong location.
4B2. Sam moves the card to the correct location.
4B3. Dave sees the card moved by Sam, and sees it snap back to its original location.
4B4. Dave moves the card to the location demonstrated by Sam.

Alternative Flow 4C

4C1. Dave does not respond X times.
4C2. Go to 3 (The PC repeats the instruction).

Alternative Flow 4D (Collaboration)

4D1. Dave does not respond Y times.
4D2. The system informs Sam.
4D3. Sam assists Dave in getting started.

Alternative Flow 4D

4D1. Dave does not respond Z times.
4D2. The system informs the teacher.
4D3. The teacher assists Dave in getting started, or pauses or terminates the exercise.

7.2 Mainstream Learning Experience examples

7.2.1 Learning goal: Programming skills

Table 2: Learning experience example (ME) – Learning goal: Programming skills (improvement)

SLA	Learning Actions	PA	Materialization	Key Moments	Relation to Achievement	Time Thre-shold
Sequencing	Sort cards into logical order.	IWB Tablet PC	Put cards into correct sequence for pelican crossing.	Students begin the interaction	Start of learning, initial setup	None
				Cards appear on screen in randomised order. Students are instructed to put their cards in correct sequence	Understand the task	None
				Students drag cards into correct sequence	Collaborate in sequencing items	None
				Students indicate when finished	Show correct sequencing of events	None
				The system responds with congratulation or correction	Feedback on success, failure or inactivity	None
				Repeat for the predetermined number of times	Completion => LA achieved	None