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D3.3 The AugMENTOR Learner Profile

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Table of contents

1 Introduction 7

1.1 Scope and objectives of the deliverable 7

1.2 Target audiences and relation to other tasks and deliverables 7

1.3 Terminology 7

2 Methods 9

2.1 Requirements elicitation 9

2.1.1 Requirements elicitation via project scope 10

2.1.2 Requirements elicitation via stakeholder analysis 10

2.1.3 Requirements elicitation via meta-review 11

2.2 Conceptual design methodology 11

3 The augMENTOR Learner Model 13

3.1 The cognitive domain 15

3.1.1 Learner characteristics in the cognitive domain 15

3.2 Learner characteristics in the affective domain 17

3.2.1 Learner characteristics in the affective domain 17

3.3 Transversal skills 18

4 Operationalization of the augMENTOR LM 19

4.1 Mapping indicators with learning platform data 19

4.1.1 The cognitive domain 19

4.1.2 The affective domain 20

4.1.3 The transversal skills 20

4.2 The augMENTOR LM interaction loop 21

5 Refinement and finalization of the augMENTOR LM 22

5.1 Formative evaluation of the augMENTOR LM 22

5.2 Findings from the formative evaluation 22

6 Limitations of the augMENTOR LM 24

7 Conclusion 25

Annex I - Meta-review findings 34

Annex II - A conceptual overview of the augMENTOR Learner Model 35

List of figures

Figure 1. Methodological process for T3.3 9

Figure 2. LM design framework [1] 12

Figure 3. The augMENTOR LM Overview 14

Figure 4. The cognitive domain and its' learner characteristics 15

Figure 5. The affective domain and its LCs 17

Figure 6. The transversal skills domain and its LCs 18

Figure 7. The augMENTOR LM activity diagram 21

List of tables

Table 1. The impact of augMENTOR on the identified target groups 9

Table 2. Experts' evaluation of the augMENTOR LM 22

List of acronyms

Acronym	Description
augMENTOR	Augmented Intelligence for Pedagogically Sustained Training and Education
augMENTOR LM	augMENTOR reference LM
CSCL	Computer Supported Collaborative Learning
LC	Learner Characteristics
LM	Learner Model
LMS	Learner Management Systems
LO	Learning Objective
MuMoMe	Multi-Store Model of Memory
NLP	Natural Language Processing
SDT	Self-Determination Theory

Executive summary

This deliverable (D3.3) reports on the activities under Task T3.3 (Development of a Reference Learner Profile). Task 3.3 acts as an interface between WP3 and WP5 and addresses the modeling of the learner's profile in diverse educational scenarios, using information about the learner’s knowledge state and cognitive characteristics, actions and practices, their behaviour and their competencies. The reference learner profile refers to the blueprint or the conceptual architecture of the learner model designed in the context of the augMENTOR project.

To develop the augMENTOR reference learner profile, we combined a top-down and bottom-up approach: combining learning and pedagogical theories, and data-driven research on quantitative indicators for modeling learning, affect, and transversal skills. Having this reference learner model as a guiding framework, the augMENTOR solution will be able to establish and retrieve dynamic learner profiles to support different contexts and diverse learner needs.

The implementation, evaluation and cross-validation of the reference learner profile using quantitative methods will be carried out and further reported in the respective deliverables of the work packages WP5 and WP6.

1 Introduction

1.1 Scope and objectives of the deliverable

This deliverable describes the activities carried out in T3.3 with the objective of developing the augMENTOR reference learner profile, a dedicated model that aims to provide dynamic information and assessments regarding learners' states. Thus, from here on, we refer to the augMENTOR reference learner profile as the augMENTOR learner model or the augMENTOR LM. The main objectives of this deliverable are:

1. to "provide the theoretical grounding upon which the foreseen augMENTOR solution will be based and assessed" while including information "about a learner's knowledge, actions, competencies, practices, behaviour, alternative collaboration modes, and cognitive characteristics" (see Chapter 3: The augMENTOR Learner Model)
2. to "design quantitative indicators for modeling knowledge, mastery, affect, collaborative and social skills and retrieve reference profiles from data which can be mapped or grounded using the proposed pedagogical framework" (see Chapter 4: Operationalization of the augMENTOR LM).

1.2 Target audiences and relation to other tasks and deliverables

This deliverable D3.3 targets stakeholders involved or affected by the augMENTOR LM and its design process. This includes project partners involved in WP3 - "Pedagogical Framework for Emerging Technologies," WP4 - "Critical Thinking and Creativity," WP5 - "AI-boosted Blended Learning Platform," and WP6 - "Use Case Deployment, Operation, Validation, and Assessment." The output of D3.3 is expected to serve as input for the tasks of WP5 and WP6. We foresee the need for cross-validation and evaluation of the work carried out under T3.3 during the pilot phase of the project. Therefore, we aim to potentially consider a refined version of the augMENTOR LM and UDE will follow up with an evaluation in deliverable D5.2 ("The AI-boosted augMENTOR platform").

1.3 Terminology

Here, we provide definitions for key terms used in this deliverable to establish a common understanding.

Personalized Learning: While the definition of personalization varies [1], one commonly referenced definition was provided in 2010 by the US Department of Education, which defined personalization as "instruction that is paced to learning needs, tailored to learning preferences, and tailored to the specific interests of different learners" [2].

Learner Model (also called Student Model): A Learner Model (LM) is an abstract representation of the learner's cognitive and non-cognitive characteristics, which is maintained by an adaptive system [3;37]. An LM is central to personalized learning.

Learner characteristics: Learner characteristics (LCs) are variables in an LM, such as learner traits, preferences, and abilities, that can potentially explain the variance in learning outcomes [6].

Indicators: Indicators are directly observable and quantifiable constructs that affect learner characteristics. Indicators are processed information which permits the study of the learning process [7].

2 Methods

Figure 1 depicts the methodological process followed in T3.3 for the design of the augMENTOR LM. Following a top-down approach, we elicited requirements for the augMENTOR LM from, a) the project's scope (see section 0); b) the augMENTOR stakeholders, as delivered in D2.1 (see section 2.1.2); and, c) the state-of-the-art as depicted by a meta-review of recent literature on LMs (see section 2.1.3). Based on the requirements analysis and following the framework of Bernacki et al. [1] (see section 2.2), we delivered the conceptualized augMENTOR LM (Chapter 3), which was then enriched, following a bottom-up approach, with indicators deriving from established studies and from data labels provided from T 5.1 (Chapter 4).

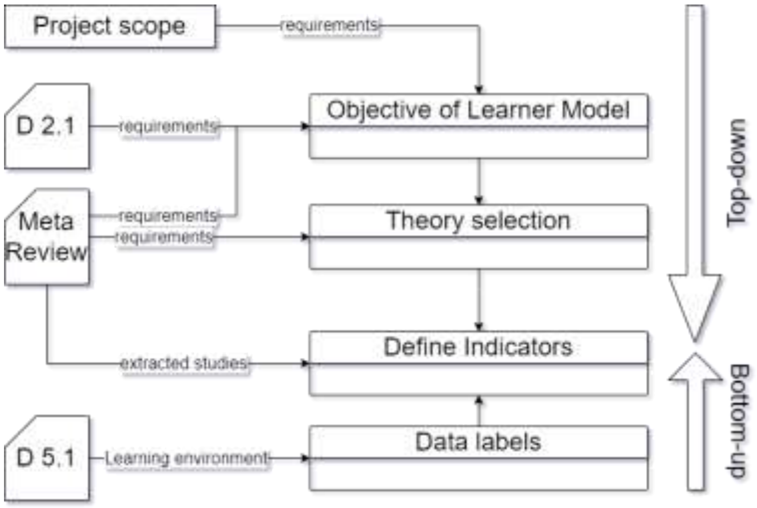

Figure 1. *Methodological process for T3.3*

2.1 Requirements elicitation

An overview of all the requirements is presented in Table 1 below.

Table 1. *The impact of augMENTOR on the identified target groups*

Requirement ID	Short description
Project Scope	
PS1	The LM must be domain-agnostic.
PS2	The LM should avoid the use of multimodal data from sensors.
PS3	The LM should refrain from or, at least, not depend solely on "self-report methods" or "survey methods" where possible.

Stakeholder Analysis	
SA1	The LM should ensure continued engagement and learning post-course
SA2	The LM should prioritize inclusivity and accessibility
SA3	The LM should personalize learning and provide adaptive feedback
SA4	The LM should monitor and nurture student motivation and engagement
SA5	The LM should enhance formative assessment and understanding of learner profiles.
Meta-review	
MR1	The LM should have a robust theoretical foundation for selecting LCs, allowing for the extraction of actionable insights regarding the learner.
MR2	The LM should rely on evidence-based indicators to accurately represent the LCs

2.1.1 Requirements elicitation via project scope

The scope of the project presupposes a set of requirements that should be considered in the design of the augMENTOR LM. These requirements are stated below:

[PS1]: The LM must be domain-agnostic.

The augMENTOR project addresses four diverse sets of pilots. The LM, therefore, should be sufficiently generalizable to be implemented in the context of all current pilots and accommodate the needs of future ones.

[PS2]: The LM should avoid the use of multimodal data from sensors.

The augMENTOR project's scope is limited to traditional desktop-based learning environment data, such as the data collected from Learning Management Systems (LMS). Consequently, intrusive sensors, which are challenging to deploy on a large scale [8], should be avoided.

[PS3]: The LM should refrain or, at least, not depend solely on "self-report methods" or "survey methods" where possible.

The collection of learner data using manual methods, such as surveys, can be monotonous and prone to error over time. Such methods also disrupt the learning process, decreasing motivation and requiring substantial time to complete [9]. Therefore, the augMENTOR LM should primarily rely on automated data mining approaches to the extent possible.

2.1.2 Requirements elicitation via stakeholder analysis

Five (5) thematic requirements for the augMENTOR LM in T3.3 were elicited in D2.1 and are briefly outlined below.

[SA1]: Ensuring continued engagement and learning post-course:

The LM must account for the engagement and learning even after the course has concluded. To keep students engaged in the learning activities in the post-course phase, the LM must actively encourage and prompt students to continue learning.

[SA2]: Prioritizing inclusivity and accessibility:

The LM must accommodate diverse, encompassing learner requirements and provide equitable learning experiences for all. Thus, the LM must deviate away from a "one-size-fits-all" tendency and emphasize the learners' individual characteristics in the design.

[SA3]: Personalized learning and adaptive feedback:

The LM must provide actionable insights on the learning process such that actionable feedback can be derived from them.

[SA4]: Monitoring and nurturing student motivation and engagement:

As motivation and engagement are essential drivers of learning, the LM must facilitate their monitoring and nurturing.

[SA5]: Enhancing formative assessment and understanding of learner profiles:

The LM must be dynamic to support formative assessment of learners' progress. In the context of educational scenarios as prescribed by the micro-level of the augMENTOR pedagogical framework (see D3.1), it is indispensable to monitor learners' cognitive states to facilitate the selection and deployment of instructional strategies that address their individual needs and foster high-level competencies such as transversal skills

2.1.3 Requirements elicitation via meta-review

We conducted a meta-review of existing literature reviews on learner modeling published in recent years (2019-2023). We selected six (6) publications which we considered relevant [10,11,8,1,12, and 13] and synthesized their findings, briefly presented in **Annex I - Meta-review** findings. In agreement with the considerations of the state-of-the-art, we formulated the following requirement deriving from the literature:

[MR1]: the augMENTOR LM should have a robust theoretical foundation for the selection of LCs, such that actionable insights regarding the learner can be extracted.

[MR2]: the augMENTOR LM should rely on evidence-based indicators to accurately represent the LCs.

2.2 Conceptual design methodology

The augMENTOR LM design adopts the framework proposed by Bernacki et al. [1] in its design process (see Figure 2). This holistic framework supports the personalization of learning environments. It defines LMs as a collection of contextually meaningful theory-driven LCs that must be monitored to incorporate personalization into the learning environment. The authors of the framework urge to select LCs based on learning theory and consider how the selected

LCs may impact or inform the adaptation of the learning environment. In the context of augMENTOR, such adaptations could be, for example, the visualization of activity metrics or recommendations provided via the user interface.

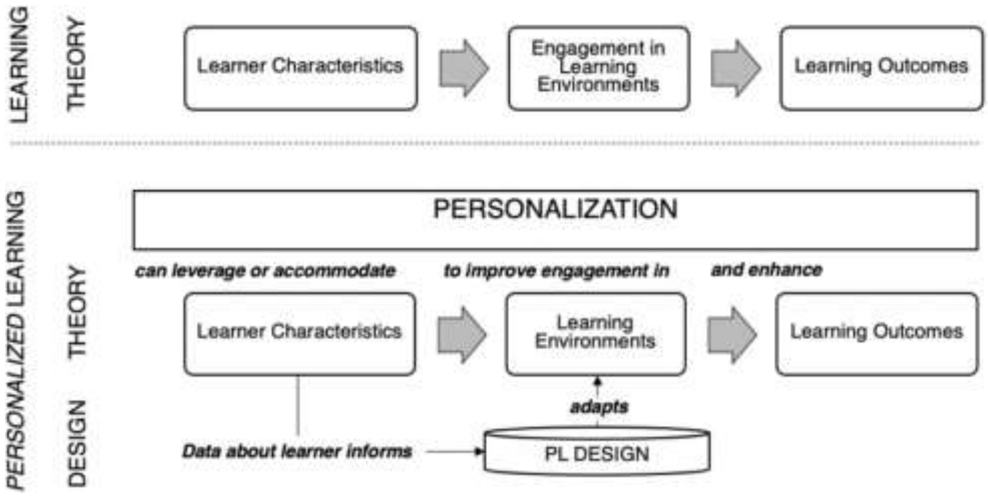

Figure 2. *LM design framework [1]*

As a high-level top-down framework, it does not dictate how to select and implement indicators for LCs. It can be argued that their emphasis on the relationship between LCs and the learning environment (as seen in Figure 2) approach insinuates an evidence-informed selection of indicators for each LC, as recommended by Abyaa et al. [13]. Despite the lack of evidence in this context [8], we have, to the fullest extent of our capabilities, relied on evidence from established research studies to define indicators for LCs in the augMENTOR LM. In a latter bottom-up approach (see Chapter 4), these indicators are populated with the data available from the digital learning environment that facilitates the activity, specifically those used by the augMENTOR pilots.

3 The augMENTOR Learner Model

As stated in the section 2.2, the augMENTOR LM adopts the framework proposed by Bernacki et al. [1]. The framework prescribes a theory-driven design of an LM, that is, a theory-driven selection of LCs. Nevertheless, the selection of theory itself is dictated by the Learning Objectives (LOs) at hand. In the case of augMENTOR and considering the requirements drawn in section 2.1, we outline a generic but fundamental LO to guide the design of the augMENTOR LM.

[LO1]: The learner must be able to recall relevant information which is a priori for all higher-order skills such as critical thinking, creativity, etc [14].

The augMENTOR LM must be able to quantify learning so that the learning environment can proactively "predict" learning success and intervene when necessary. In addition, the augMENTOR LM must also monitor learners' motivation to continuously engage in the learning tasks, which is necessary for information retention and recall.

LO1 demonstrates the critical role of two high-level domains of learning: the cognitive domain and the affective domain. Figure 3 below is an overview of the augMENTOR LM. In the following, we outline the design of the augMENTOR LM in accordance with these two domains. Additionally, we touch upon the aspects of transversal skills in the augMENTOR LM.

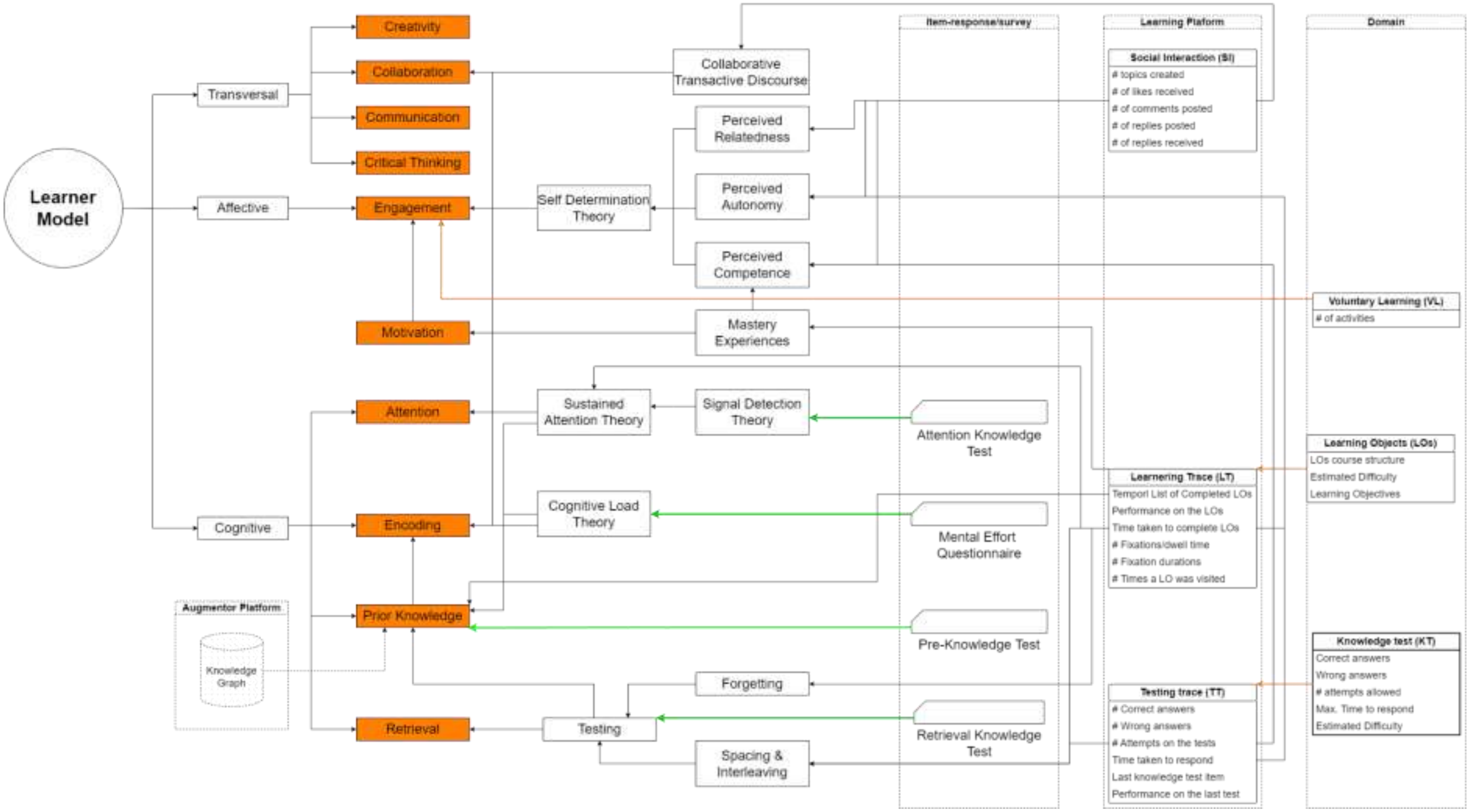

Figure 3. *The augMENTOR LM Overview*

3.1 The cognitive domain

Kirschner, Sweller, and Clark [15] defined "cognitive learning" as the lasting change in long-term memory." Learning occurs because of the assimilation of new information or manipulation of existing knowledge in long-term memory, such that it results in enhanced recall of information. The Multi-store Model of Memory (MuMoMe) describes how information is processed through various memory types before it is stored in long-term memory. We adopted the MuMoMe as a theoretical foundation [according to meta-review requirement MR1, project scope requirement PS1] to guide the selection of the LCs in the cognitive domain of augMENTOR LM. The selected LCs monitor the learner's cognitive states to support the educators in better informing the design of educational scenarios [according to stakeholder analysis requirement SA3, SA5]. A brief account of the MuMoMe is provided in **Annex II - A conceptual overview of the augMENTOR Learner** Model.

3.1.1 Learner characteristics in the cognitive domain

The following sections list the selected LCs grounded on the MuMoMe and their respective evidence-based indicators that we encountered in the literature. These LCs (highlighted in orange) are presented in Figure 4. We first identified LCs that are meaningful in terms of information storage in long-term memory, i.e., cognitive learning. Second, we identified indicators corresponding to the LCs based on evidence found in the literature. In the following, the LCs and their indicators are illustrated according to the critical processes in the MuMoMe. We would like to remark here that an indicator in this context is a description of expected data and not the data itself. Specific data fields are addressed in the section 4.1 (Mapping indicators with Moodle data). In addition, where relevant, we also highlight the relationships between various LCs throughout the augMENTOR LM. An extended discussion on the selected LCs and the related literature is presented in **Annex II - A conceptual overview of the augMENTOR Learner** Model.

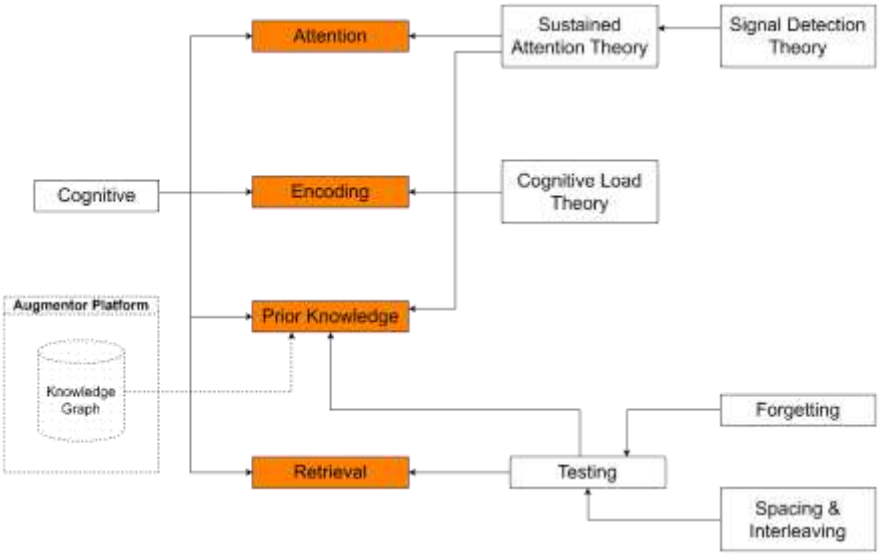

Figure 4. *The cognitive domain and its' learner characteristics*

Attention: According to the MuMoMe, paying attention to the incoming information facilitates the transfer of the information from the sensory memory to the short-term memory. The augMENTOR LM utilises the Signal Detection Theory [16], according to which sustained attention can be measured in terms of the correctness of the response and the time taken to respond. For example, a delayed response may indicate that the learner is not familiar with the learning material or is not entirely focused on the learning activity.

Encoding: Incoming information undergoes encoding in the working memory, which results in the storage of processed information in the long-term memory. According to the Cognitive Load Theory (CLT) [17], the encoding process imposes "Cognitive Load" (CL) on the working memory. However, cognitive overload can impede learning, thereby underscoring the importance of monitoring CL in the augMENTOR LM. Evidence in regard to the non-sensor-based indicators of CL is sparse as most studies measuring CL often tend to use subjective methods [18], such as the single-item numerical scale by Paas et al. [19]. As this instrument by Paas et al. [19] only contains a single item, it fits within the project scope requirement (PS3) we defined in section 2.1 (Requirements Elicitation). We propose using the Experience Sampling Method by Hektner et al. [20], in which the item will be administered every time a learner is engaged in the learning activity over time. The CL trace generated over time is significantly associated with the perceived CL of the learner [21].

Prior Knowledge: The most common method of personalization was to provide an adaptive experience based on learners' prior knowledge [1], and it is a significant indicator of learning [1,22]. Prior Knowledge is also vital to support learning in the micro-level educational scenarios defined in the augMENTOR pedagogical framework (see D3.1). To assess prior knowledge, a knowledge test can be administered at the start to initialise the learners' Prior Knowledge (as done by Ferreira Da Rocha et al., [23]), after which it is updated based on the student's performance in tests and quizzes, which are quintessential components of every learning experience.

Retrieval: The information, once stored in the long-term memory, is prone to forgetting. Therefore, in the long term, it is crucial to monitor if the learners are still able to successfully retrieve specific information from long-term memory. Successful retrieval of information from long-term memory is a prerequisite for higher-order learning processes such as the transfer of knowledge and transversal skills [14]. Retrieval practice can be implemented as a function of learners' performance in retrieval tests or quizzes (see Testing-trace in Figure 3). Such tests are prompted to students based on how long ago the student last visited the concept, i.e., forgetting and spacing, and other related concepts studied, i.e., interleaving. Such prompts also ensure continued engagement and learning post-course. (see stakeholder analysis requirement SA1)

3.2 Learner characteristics in the affective domain

Fariani et al. [10] recommended exploring the affective domain in LMs after they found no studies discussing affective aspects, such as emotions and motivation, in their review. The affective domain of learning emphasizes the role of emotional engagement in shaping cognitive processes. A multitude of researchers acknowledge that emotions directly affect memory [24, 25, 26]. Similarly, other affective factors, such as motivation and engagement, have been regarded as some of the strongest predictors of learning [27, 28]. Thus, the augMENTOR LM aims to include an affective dimension in its core design [see stakeholder analysis requirements SA1, SA4].

3.2.1 Learner characteristics in the affective domain

We emphasize the affective domain (see Figure 5) in augMENTOR by modelling "Motivation" and "Engagement" in the augMENTOR LM [see stakeholder analysis requirement SA1, SA4]. An extended discussion and the related literature are presented in **Annex II - A conceptual overview of the augMENTOR Learner** Model.

Specifically, we perceive motivation as a significant driver of engagement in learning [29] and, thus, as a mediating factor for engagement. Motivated and engaged learners achieve superior learning [30].

The "Engage Taxonomy" by Cristea et al. [31] provides metrics for measurable engagement in MOOCs based on the "Self-determination theory (SDT)" [32]. Therefore, it is well suited for our objectives in augMENTOR to account for modeling of both affective and social factors, as the SDT studies motivation at a social level.

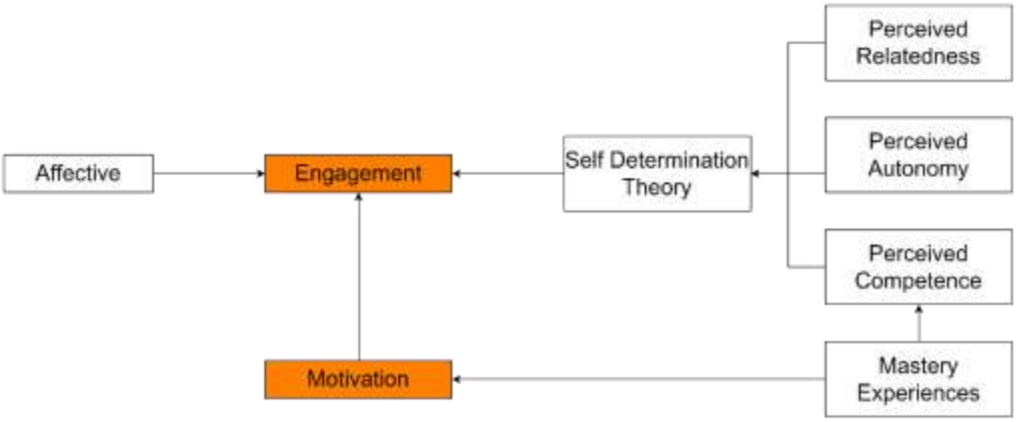

Figure 5. *The affective domain and its LCs*

3.3 Transversal skills

In the context of the augMENTOR LM, we propose the modelling of transversal skill - and in particular, Communication, Critical Thinking, Collaboration, and Creativity (4Cs)- separately from cognitive and affective aspects (see Figure 3). As established in WP4 "Critical Thinking and Creativity", the transversal skills we address in augMENTOR, are evaluated primarily with the use of rubrics (will be reported in D4.3: "Methods and tools for the enhancement and assessment of 21st-century competencies"), due to a lack of validated frameworks that relate data-driven approaches to the assessment of Communication, Critical Thinking, and Creativity [4] (also see D4.1, "Creative Pedagogy in the augMENTOR solution"). However, substantial work has been carried out regarding the automatic assessment of Collaboration [33,34] - as part of research in the area of Computer-Supported Collaborative Learning (CSCL). However, these works do not explicitly relate collaboration with cognitive or affective domains of learning. We acknowledge these research gaps in augMENTOR LM (see Figure 6) and have taken them into account for the operationalization of the Collaboration in the augMENTOR LM. More specifically, we model collaboration based on two core constructs, i.e., collaborative cognitive load theory and collaborative transactive discourse. We further elaborate on these constructs and other transversal skills in **Annex II - A conceptual overview of the augMENTOR Learner** Model.

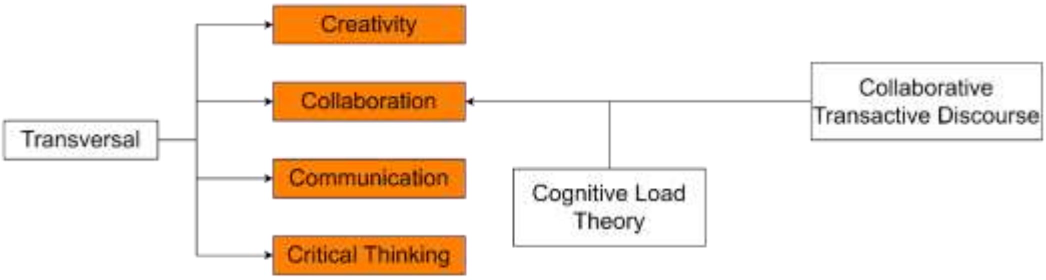

Figure 6. *The transversal skills domain and its LCs*

4 Operationalization of the augMENTOR LM

To operationalize the augMENTOR LM, we followed a bottom-up approach that emphasizes the data-driven aspects of modelling learning and ensures that the scalability considerations and technical feasibility are maintained. To that end, we referred to the database schema from T5.1 (see Database schema for augMENTOR [71]), which collects all the potential data fields from the augMENTOR chosen LMS (for example, Moodle) and mapped them according to the indicators accompanying the LCs, as presented in Chapter 3. To enable common understanding, we made explicit use of data headers listed in T5.1 where available (here seen in italics). We want to note that the augMENTOR LM proposes "informed" indicators or methods to calculate these indicators when evidence is lacking, or the data is missing from the schema of T5.1.

4.1 Mapping indicators with learning platform data

In the following, we list a non-exhaustive set of indicators for each LCs and describe their contribution to the measure of LCs, according to the augMENTOR LM.

4.1.1 The cognitive domain

Attention: To measure sustained attention, a single knowledge test or quiz is administered during the learning activity and relevant data are collected in the [*mdl_quiz*] category. The learners must respond to the quiz within the [*mdl_quiz, timelimit*], and only one attempt is allowed. The time taken to respond is calculated as the difference of [*mdl_quiz_attempts, timestart, timefinish*]. The correctness of the answer is reflected in the grade.

Encoding: Encoding is measured using the Cognitive Load Theory (CLT) questionnaire [*mdl_survey, mdl_questions*]. The survey item pertains to the learning activity within a course [*mdl_survey, id, course*]. The learners' response to the survey [*mdl_answers, answer1*] is used to temporally map the learners' cognitive load.

Prior Knowledge: Prior knowledge can be measured using a pre-knowledge test, using data collected from [*mdl_quiz, mdl_quiz_attempts, mdl_quiz_feedback*]. However, as stated in Chapter 3, the granularity and, consequently, the method for modelling prior knowledge depends on the context of the application. For example, prior knowledge, in theory, can be simply represented by the history of learning activities undertaken, or it can also be represented by topic modelling [*mdl_mindmap, mdl_forum_discussions, mdl_forum_posts*], etc.

Retrieval: Retrieval is measured by modeling the forgetting and the testing effect. To measure retrieval, recurring knowledge tests or quiz is administered and relevant data are collected in the [*mdl_quiz, mdl_quiz_attempts, mdl_quiz_grades*] category. Forgetting is modelled for each quiz and course the learner undertakes, based on the date [*mdl_quiz, id, name*], [*mdl_quiz_attempts, timefinish*] the quiz was last revisited. After each consecutive revisit, if the learner's performance [*mdl_quiz_attempts, sumgrades*] is satisfactory, the administration of the quiz the next time should be extended with a longer duration. On the other hand, if the learner's [*mdl_quiz_attempts, sumgrades*] are not satisfactory despite the number of allowed re-attempts, the prior knowledge of the learner should be updated accordingly.

4.1.2 The affective domain

Motivation and engagement are measured using the Engage Taxonomy, which also provides validated indicators for modeling Autonomy, Relatedness and Competence. While those indicators are primarily extracted from MOOCs and focused on online collaboration, most LMS platforms provide similar collaborative features.

Autonomy can be modelled using the number of unique learning activities [*mdl_h5pactivity*] undertaken per week, the number of attempts to answer a quiz [*mdl_quiz_attempts, uniqueid*], number of parent posts in a discussion [*mdl_forum_posts, userid, parent*], number of replies to parent posts [*mdl_forum_posts, userid, parent*] and their polarity (postive, neutral, negetive) which can be extracted by sentiment analysis, and the replies made to original posts under a discussion [*mdl_forum_posts, parent, userid*].

Competence can be modelled using the number of correct and incorrect answers [*mdl_quiz_attempts, sumgrades*] to a quiz, the number of replies to a parent post [mdl_forum_posts, userid, parent], and the number of positive replies posted and received [*mdl_forum_posts, userid, parent*].

Relatedness can be modelled using the number of parent post in a discussion [*mdl_forum_posts, userid, parent*] and their polarities (postive, neutral, negetive), number of replies posted and received to a parent post [*mdl_forum_posts, userid, parent*] and their polarities.

4.1.3 The transversal skills

As aforementioned, skills such as creativity, communication and critical thinking will be evaluated in augMENTOR with the use of rubrics (D4.1, "Creative Pedagogy in the augMENTOR solution Interim", D4.3: "Methods and tools for the enhancement and assessment of 21st-century competencies"). However, the modular and flexible nature of the augMENTOR LM allows the integration of data-driven assessments if and when automatic methods for assessing such skills are available, they can be related to cognitive or affective aspects of learning.

As a proof of concept, we model collaboration in terms of the cognitive load as described in section 4.1.2. Additionally, we model transactive discourse in terms of the number of parent posts in a collaboration discussion board and the number of replies to parent posts [*mdl_forum_posts, user-id, parent*]. Forward looking, one could argue for advanced Natural Language Processing (NLP) methods, such as keyword extraction from the textual input in the posts, and its corresponding replies, to measure the similarity between them. This should provide an estimate of the link between ideas which is vital during the collaborative process.

4.2 The augMENTOR LM interaction loop

Below, we briefly outline a core interaction loop of the augMENTOR LM in the form of an activity diagram. Figure 7 below highlights a series of events that a learner undertakes from logging into the LMS and logging out. The figure depicts the active nature of the LM, which prompts the learner to respond to various survey-based data collection while others are collected in a stealth manner. Immediately after the learner logs into the LMS and starts to engage with the learning activity, they are prompted to answer a question selected by the retention test module. If the response is incorrect, the LM updates the prior knowledge accordingly and provides the correct answer. The learner engages with the learning task during which items from experience sampling are prompted accordingly. Finally, when the learner is finished, they will undertake a test corresponding to the learning object.

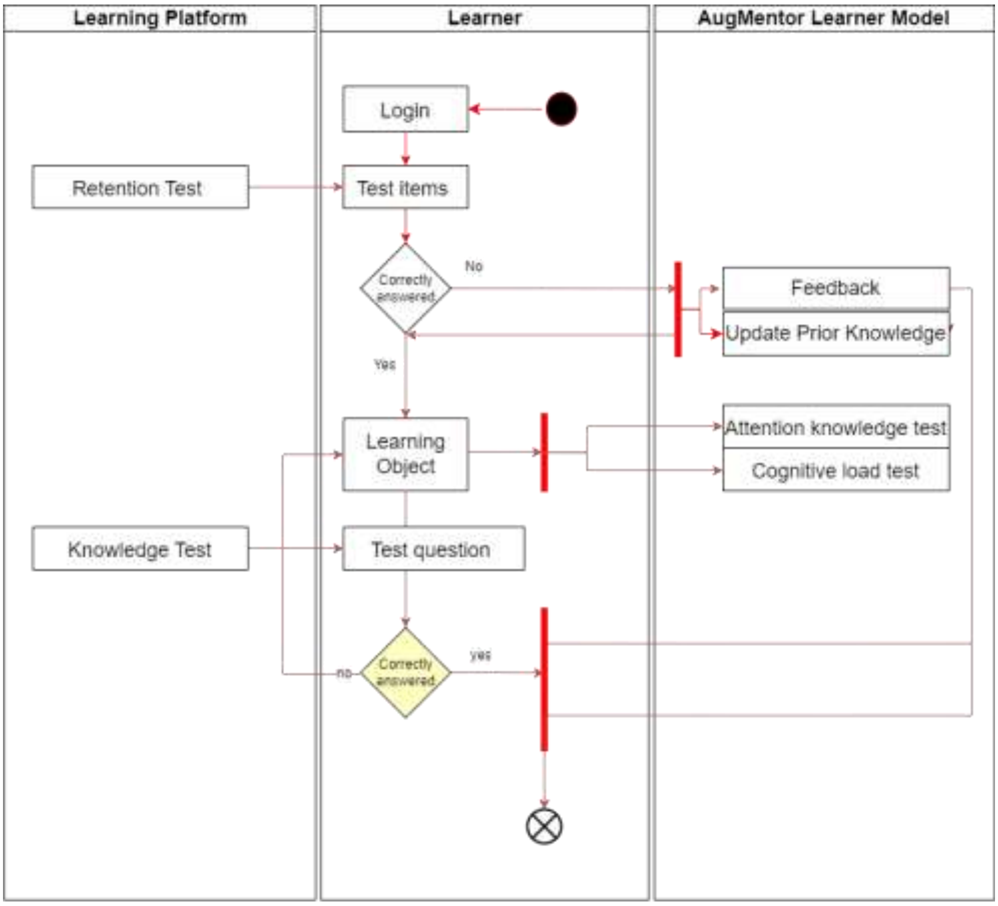

Figure 7. *The augMENTOR LM activity diagram*

5 Refinement and finalization of the augMENTOR LM

5.1 Formative evaluation of the augMENTOR LM

The augMENTOR LM is in the conceptual design and prototypical phase. Therefore, our concern was to evaluate its theoretical soundness, which we define as the notion that theory is strongly constructed and well-reasoned. Additionally, we aimed to ensure that the augMENTOR LM aligns with the pedagogical dimension of the project.

To do so, we followed a qualitative approach: we developed a questionnaire with Likert items. The questionnaire also contained space for open-text remarks below each of the items and at the bottom for overall remarks. To evaluate the augMENTOR LM, we invited two experts (augMENTOR partners) with extensive experience in theoretical research and learning science to explore the augMENTOR LM. In the first phase, the experts reviewed the questionnaire itself. The designer of the augMENTOR LM, and the questionnaire explained each of the items in the questionnaire to the experts. Their feedback was immediately adopted. Then the experts were given a walkthrough of the augMENTOR LM. During the walkthrough, the experts had the opportunity to ask questions. Then, we shared a copy of the questionnaire with the experts and asked them to fill it out. The experts returned their filled-in questionnaire, and the evaluation ended.

5.2 Findings from the formative evaluation

In the Table 2 below, we provide the ratings for each item provided by the experts. Then, we collectively discuss some of the highlights from the experts' open-text remarks.

Table 2. *Experts' evaluation of the augMENTOR LM*

Item no.	**Items**	**Rating 1-5**	
General		Expert 1	Expert 2
G1	The LM potentially contributes to educational teaching practices. *It can be used meaningfully to facilitate hybrid education.	5	4
G2	The LM provides actionable insights into the learner's learning process. *It is not a black box, and its features can be meaningfully interpreted to generate feedback.	5	4
G3	The LM is an original contribution compared to other LMs. *in regard to research, design, approach, etc.	4	5
G4	The LM can be generalised to other contexts. *It is not bound to a specific domain or context	4	5
G5	The LM is complete, and all relevant aspects are covered.		4

	*It is sufficiently self-sustaining, and no critical features are missing in its design		
Theoretical soundness		Expert 1	Expert 2
T1	The constructs in the LM are clearly defined. *All keywords and concepts have been defined concretely	4	5
T2	The underlying theories and principles are meaningful & clearly articulated *The theories used by the LM are sufficiently elaborated	4	5
T3	The LM aligns with existing theories. *The design of the LM adheres to the theoretical assumptions	4	5
T4	The assumptions of the LM are clear and consistent. *If the LM has made other independent assumptions (i.e. not inherited from theories) they have been articulated clearly	3	5
T5	The relationships between different components of the LM are clearly articulated.	3	5
T6	The LM provides the simplest explanation of the learning process. *The components in the LM are meaningful and not redundant and serve a purpose	4	4
T7	The LM is logically consistent, i.e., there are no logical fallacies that render the model erroneous *For example, if two components are contraries and negate each other, etc.		5

Regarding the General items from G1-G5, the experts were content across the items and in agreement. The experts positively remarked on the unique approach via which the augMENTOR LM manages attention. However, they also remarked on the absence of transversal skills in the LM. We addressed this by extending the LM with a collaborative branch, as seen in the section 3.1.1.

Regarding theoretical soundness, the experts rated most of the items as above average, except T4 & 5. T4 & T5 are more concerned with the documentation of the LM, which we have tried to improve. Similarly, one of the experts remarked on T1 and raised concerns regarding the concepts of the LM being potentially difficult for a non-theoretical person. While we have made efforts to simplify their description in the text, T1 is more concerned with reducing ambiguity in the way the latent constructs are instantiated.

In the overall remarks section, the experts provided two suggestions. The first suggested a closer integration with the LMS data schema proposed by T5.1, which we have extensively made efforts to comply with in the section 4.1. The second suggested simplification of the instantiation of the cognitive load theory. After much further consideration, we obliged by removing references to mental load and self-efficacy and simply measuring the perceived mental effort of the learner.

6 Limitations of the augMENTOR LM

We acknowledge that there are several limitations in the design of the LM that are either inherent due to the project's scope or derive from the methodological approach we followed.

Regarding limitations inherent to the project's scope: Multimodal data and sensor-based mechanisms are becoming increasingly common in learner modelling due to their accuracy [5] and advancements in machine learning and deep learning techniques. The augMENTOR LM is tethered to the traditional desktop use case, which limits the integration sensors for modeling the affective dimension LCs, such as emotion which has been often ignored in the learner modelling literature [11]. At the same time, sensor-free approaches using recent advancements in AI to infer learners' cognitive and affective states are promising [8] and are worth consideration for their scalability in education. Similarly, the augMENTOR LM serves the needs of diverse pilots and is, therefore, domain-agnostically designed. This also limits the model from making content-specific inferences and, consequently, is unable to provide content-related feedback.

Regarding limitations deriving from the methodological approach: The augMENTOR LM adopts a top-down theory-driven approach to modelling. The selection of theories itself is driven by the requirements of the project. However, we also inherit the limitations of such theories themselves in our LMs. For example, the MuMoMe does not sufficiently explain why some information is learnt and retained better than others [35]. Baddeley's [36] working memory model and Craik and Lockhart's [35] depth of processing model extends MuMoMe, thus addressing some of its limitations, but their implications for learner modelling remain unclear.

Similarly, the Engage Taxonomy was originally developed for MOOCs. Consequently, the indicators provided by Cristea et al. [31] were also extracted from MOOC literature. Despite our educated efforts to map the indicators from MOOC with indicators from LMS in augMENTOR, these mappings are untested. Such "best" educated guesses cannot be unearthed until the model is empirically tested. The model, parts of it or in its entirety is set to be tested in the context of D5.2 and D6.2

7 Conclusion

D3.3 details the contribution of activities undertaken in T3.3, WP3. The goal of T3.3 is to design a state-of-the-art reference learner model (LM), which we termed "The AugMENTOR Learner Model" (augMENTOR LM). The requirements for the augMENTOR LM were elicited via stakeholder analysis in D2.1, the projects' scope, and the meta-review of the latest literature. From the plethora of LM design frameworks, we adopted the design methodology from Bernacki et al. [1] to guide the design of the augMENTOR LM.

In the top-down approach, we first constructed a theoretical/conceptual LM. The LM primarily models the cognitive and affective domains but also touches upon the transversal skills. The selection of the Learner Characteristics (LCs) in the cognitive domain was guided by the Multi-store Model of Memory, which addresses four primary learner characteristics: attention, encoding, prior knowledge, and retention. These LCs may be further broken down into sub-constructs based on the theoretical definitions, where necessary. Similarly, the affective domain was modelled primarily with motivation and engagement as the core LCs. Both these LCs were modelled using the Engage Taxonomy by Cristea et al. [31]. We also ventured into the transversal skill domain by proposing a model for collaboration using the collaborative cognitive load theory.

During the bottom-up approach, we mapped the indicators extracted from the literature to the data commonly available in learning platforms. This was achieved in collaboration with the work conducted under T5.1. Each of the LCs was documented along with the indicators used in the original study. The indicators were then abstracted to map to data so that a unique definition of that particular indicator could be extracted. Finally, we mapped the LM with the data from the learning platforms using the extracted definition.

We conducted a qualitative evaluation of the augMENTOR LM with pedagogy experts. To guide the evaluation, we co-designed an instrument in the form of a questionnaire together with the experts. We followed-up with a focus group during which two experts provided several suggestions [see section 0], all of which were implemented in the LM presented in D3.3.

Following D3.3, the augMENTOR LM will be used as input for WP5 to inform and guide the implementation of the augMENTOR platform and in WP6 where it will be deployed in the upcoming pilot studies. Data collected from these pilots will allow us to validate and test the augMENTOR LM empirically. This evaluation will be reported in D5.2.

References

[1] M. L. Bernacki, M. J. Greene, and N. G. Lobczowski, “A Systematic Review of Research on Personalized Learning: Personalized by Whom, to What, How, and for What Purpose(s)?,” *Educational Psychology Review*, vol. 33, no. 4, pp. 1675–1715, Dec. 2021, doi: 10.1007/s10648-021-09615-8.

[2] “Transforming American Education National Education Technology Plan 2010 Learning Powered by Technology.” Available: http://www.ed.gov/sites/default/files/netp2010.pdf

[3] V. J. Shute and D. Zapata-Rivera, “Adaptive Educational Systems,” in *Adaptive Technologies for Training and Education*, P. J. Durlach and A. M. Lesgold, Eds. Cambridge: Cambridge University Press, 2012, pp. 7–27

[4] Dea Puspita Septiani, Panos Kostakos, Margarida Romero. “Analysis of Creative Engagement in AI Tools in Education Based on the #PPai6 Framework.” MIS4TEL 2023 - International Conference in Methodologies and intelligent Systems for Techhnology Enhanced Learning, Jul 2023, Guimaraes, Portugal. pp.48 - 58, ⟨10.1007/978-3-031-42134-1_5⟩. ⟨hal-04593531⟩

[5] J. Liang et al., "Student Modeling and Analysis in Adaptive Instructional Systems," in IEEE Access, vol. 10, pp. 59359-59372, 2022, doi: 10.1109/ACCESS.2022.3178744.

[6] L. Tetzlaff, F. Schmiedek, and G. Brod, “Developing Personalized Education: A Dynamic Framework,” *Educ Psychol Rev*, vol. 33, no. 3, pp. 863–882, Sep. 2021, doi: 10.1007/s10648-020-09570-w.

[7] C. Sauvageot, *Indicators for educational planning: a practical guide//UNESCO*. Paris: International Institute for Educational Planning. Available: https://unesdoc.unesco.org/ark:/48223/pf0000103407.locale=en

[8] M. M. Rahman, H. A. A. Salem, S. Yeom, N. Ollington, R. Ollington, and Md. M. Rahman, “A Preliminary Study on Learners’ Personal Traits for Modelling Learner Profiles in ITS: A Sensor-free Approach,” in *2023 IEEE 13th Symposium on Computer Applications & Industrial Electronics (ISCAIE)*, Penang, Malaysia: IEEE, May 2023, pp. 287–292. doi: 10.1109/ISCAIE57739.2023.10165219.

[9] F. A. Dorça, R. D. Araújo, V. C. De Carvalho, D. T. Resende, and R. G. Cattelan, “An Automatic and Dynamic Approach for Personalized Recommendation of Learning Objects Considering Students Learning Styles: An Experimental Analysis,” *Informatics in Education*, vol. 15, no. 1, pp. 45–62, Apr. 2016, doi: 10.15388/infedu.2016.03.

[10] R. I. Fariani, K. Junus, and H. B. Santoso, “A Systematic Literature Review on Personalised Learning in the Higher Education Context,” *Tech Know Learn*, vol. 28, no. 2, pp. 449–476, Jun. 2023, doi: 10.1007/s10758-022-09628-4.

[11] S. A. Ochukut, R. O. Oboko, E. Miriti, and E. Maina, “Research Trends in Adaptive Online Learning: Systematic Literature Review (2011–2020),” *Tech Know Learn*, vol. 28, no. 2, pp. 431–448, Jun. 2023, doi: 10.1007/s10758-022-09615-9.

[12] K. C. Li and B. T.-M. Wong, “Features and trends of personalised learning: a review of journal publications from 2001 to 2018,” *Interactive Learning Environments*, vol. 29, no. 2, pp. 182–195, Feb. 2021, doi: 10.1080/10494820.2020.1811735.

[13] A. Abyaa, M. Khalidi Idrissi, and S. Bennani, “Learner modelling: systematic review of the literature from the last 5 years,” *Education Tech Research Dev*, vol. 67, no. 5, pp. 1105–1143, Oct. 2019, doi: 10.1007/s11423-018-09644-1.

[14] K. Sawyer, *Zig zag: the surprising path to greater creativity*. San Francisco, Calif.: Jossey-Bass, 2013.

[15] P. A. Kirschner, J. Sweller, and R. E. Clark, “Why Minimal Guidance During Instruction Does Not Work: An Analysis of the Failure of Constructivist, Discovery, Problem-Based, Experiential, and Inquiry-Based Teaching,” *Educational Psychologist*, vol. 41, no. 2, pp. 75–86, Jun. 2006, doi: 10.1207/s15326985ep4102_1.

[16] S.-L. Hwu, “Developing SAMM: A Model for Measuring Sustained Attention in Asynchronous Online Learning,” *Sustainability*, vol. 15, no. 12, p. 9337, Jun. 2023, doi: 10.3390/su15129337.

[17] Sweller, John, Ayres, Paul, and Kalyuga, Slava, *Cognitive Load Theory*, 1st ed. in Explorations in the Learning Sciences, Instructional Systems and Performance Technologies. Springer New York, NY, 2011. [Online]. Available: https://doi.org/10.1007/978-1-4419-8126-4

[18] D. Mutlu-Bayraktar, V. Cosgun, and T. Altan, “Cognitive load in multimedia learning environments: A systematic review,” *Computers & Education*, vol. 141, p. 103618, Nov. 2019, doi: 10.1016/j.compedu.2019.103618.

[19] F. Paas, P. Ayres, and M. Pachman, “Assessment of cognitive load in multimedia learning: theory, methods and applications,” in *Recent innovations in educational technology that facilitate student learning*, D. H. Robinson and G. Schraw, Eds., in Current Perspectives on Cognition Learning and Instruction. , United States: Information Age Publishing, 2008, pp. 11–35.

[20] J. Hektner, J. Schmidt, and M. Csikszentmihalyi, *Experience Sampling Method*. Thousand Oaks, California, 2024. doi: 10.4135/9781412984201.

[21] J. Jovanović, D. Gašević, A. Pardo, S. Dawson, and A. Whitelock-Wainwright, “Introducing meaning to clicks: Towards traced-measures of self-efficacy and cognitive load,” in *Proceedings of the 9th International Conference on Learning Analytics & Knowledge*, Tempe AZ USA: ACM, Mar. 2019, pp. 511–520. doi: 10.1145/3303772.3303782.

[22] P. C. Brown, H. L. Roediger, and M. A. McDaniel, *Make It Stick*. Harvard University Press, 2014. doi: 10.2307/j.ctt6wprs3.

[23] F. D. Ferreira Da Rocha *et al.*, “Gamification and open learner model: An experimental study on the effects on self-regulatory learning characteristics,” *Educ Inf Technol*, Jun. 2023, doi: 10.1007/s10639-023-11906-2.

[24] L. Jiang, Y. Wang, and Y. Yang, “How Different Emotions Affect Semantic Memory,” vol. 615.

[25] A. S. Petrucci and D. J. Palombo, “A matter of time: how does emotion influence temporal aspects of remembering?,” *Cognition and Emotion*, vol. 35, no. 8, pp. 1499–1515, Nov. 2021, doi: 10.1080/02699931.2021.1976733.

[26] C. M. Tyng, H. U. Amin, M. N. M. Saad, and A. S. Malik, “The Influences of Emotion on Learning and Memory,” *Front. Psychol.*, vol. 8, p. 1454, Aug. 2017, doi: 10.3389/fpsyg.2017.01454.

[27] S. I. Ramírez Luelmo, N. El Mawas, and J. Heutte, “Towards Open Learner Models Including the Flow State,” in *Adjunct Publication of the 28th ACM Conference on User Modeling, Adaptation and Personalization*, Genoa Italy: ACM, Jul. 2020, pp. 305–310. doi: 10.1145/3386392.3399295.

[28] P. G. de Barba, G. E. Kennedy, and M. D. Ainley, “The role of students’ motivation and participation in predicting performance in a MOOC,” *Journal of Computer Assisted Learning*, vol. 32, no. 3, pp. 218–231, 2016, doi: https://doi.org/10.1111/jcal.12130.barba

[29] F. A. Orji, “Modelling and Quantifying Learner Motivation for Adaptive Systems: Current Insight and Future Perspectives”.

[30] M. Becker, N. McElvany, and M. Kortenbruck, “Intrinsic and extrinsic reading motivation as predictors of reading literacy: A longitudinal study.,” *Journal of Educational Psychology*, vol. 102, no. 4, pp. 773–785, 2010, doi: 10.1037/a0020084.

[31] A. I. Cristea *et al.*, "The engage taxonomy: SDT-based measurable engagement indicators for MOOCs and their evaluation," *User Model User-Adap Inter*, Aug. 2023, doi: 10.1007/s11257-023-09374-x.

[32] R. M. Ryan and E. L. Deci, "Self-Determination Theory," in *Encyclopedia of Quality of Life and Well-Being Research*, F. Maggino, Ed., Cham: Springer International Publishing, 2022, pp. 1–7. doi: 10.1007/978-3-319-69909-7_2630-2.

[33] I.-A. Chounta and N. Avouris, "Towards the real-time evaluation of collaborative activities: Integration of an automatic rater of collaboration quality in the classroom from the teacher's perspective," *Education and Information Technologies*, vol. 21, no. 4, pp. 815–835, Jul. 2016, doi: 10.1007/s10639-014-9355-3.

[34] S. Praharaj, M. Scheffel, M. Schmitz, M. Specht, and H. Drachsler, "Towards Collaborative Convergence: Quantifying Collaboration Quality with Automated Co-located Collaboration Analytics," in *LAK22: 12th International Learning Analytics and Knowledge Conference*, in LAK22. New York, NY, USA: Association for Computing Machinery, 2022, pp. 358–369. doi: 10.1145/3506860.3506922.

[35] F. I. M. Craik and R. S. Lockhart, "Levels of processing: A framework for memory research," *Journal of Verbal Learning and Verbal Behavior*, vol. 11, no. 6, pp. 671–684, 1972, doi: https://doi.org/10.1016/S0022-5371(72)80001-X.

[36] A. D. Baddeley, *Human memory: Theory and practice*. in Human memory: Theory and practice. Needham Heights, MA, US: Allyn & Bacon, 1990, pp. xi, 515.

[37] H. Sun, Q. Zheng, H. Zhang, and H. Pan, "Learner Modeling Framework Based on Learning Analytics," in *2022 IEEE 2nd International Conference on Data Science and Computer Application (ICDSCA)*, Dalian, China: IEEE, Oct. 2022, pp. 64–68. doi: 10.1109/ICDSCA56264.2022.9988517.

[38] M. Vandewaetere, P. Desmet, and G. Clarebout, "The contribution of learner characteristics in the development of computer-based adaptive learning environments," *Computers in Human Behavior*, vol. 27, no. 1, pp. 118–130, Jan. 2011, doi: 10.1016/j.chb.2010.07.038.

[39] R. C. Atkinson and R. M. Shiffrin, "Human Memory: A Proposed System and its Control Processes," K. W. Spence and J. T. Spence, Eds., in Psychology of Learning and Motivation, vol. 2. , Academic Press, 1968, pp. 89–195. doi: https://doi.org/10.1016/S0079-7421(08)60422-3.

[40] S.-L. Hwu, “Developing SAMM: A Model for Measuring Sustained Attention in Asynchronous Online Learning,” *Sustainability*, vol. 15, no. 12, p. 9337, Jun. 2023, doi: 10.3390/su15129337.

[41] J. B. Krakow and C. B. Kopp, “The Effects of Developmental Delay on Sustained Attention in Young Children,” *Child Development*, vol. 54, no. 5, pp. 1143–1155, 1983, doi: 10.2307/1129670.

[42] E. Isbell, S. D. Calkins, M. M. Swingler, and E. M. Leerkes, “Attentional fluctuations in preschoolers: Direct and indirect relations with task accuracy, academic readiness, and school performance,” *Journal of Experimental Child Psychology*, vol. 167, pp. 388–403, Mar. 2018, doi: 10.1016/j.jecp.2017.11.013.

[43] B. H. Limbu, H. Jarodzka, R. Klemke, and M. Specht, “Can You Ink While You Blink? Assessing Mental Effort in a Sensor-Based Calligraphy Trainer,” *Sensors*, vol. 19, no. 14, p. 3244, 2019, doi: 10.3390/s19143244.

[44] K. Ouwehand, A. V. D. Kroef, J. Wong, and F. Paas, “Measuring Cognitive Load: Are There More Valid Alternatives to Likert Rating Scales?,” *Front. Educ.*, vol. 6, p. 702616, Sep. 2021, doi: 10.3389/feduc.2021.702616.

[45] A. Çebi and T. Güyer, “Modeling of relationships between students’ navigational behavior and problems in hypermedia learning system: the moderating role of working memory capacity,” *Interactive Learning Environments*, vol. 30, no. 3, pp. 552–567, Feb. 2022, doi: 10.1080/10494820.2019.1674881.

[46] T.-W. Chang, M. M. El-Bishouty, S. Graf, and Kinshuk, “An Approach for Detecting Students’ Working Memory Capacity from Their Behavior in Learning Systems,” in *2013 IEEE 13th International Conference on Advanced Learning Technologies*, Beijing, China: IEEE, Jul. 2013, pp. 82–86. doi: 10.1109/ICALT.2013.29.

[47] A. Kumar and V. Bharti, “Contribution of Learner Characteristics in the Development of Adaptive Learner Model,” in *Intelligent Communication, Control and Devices*, vol. 989, S. Choudhury, R. Mishra, R. G. Mishra, and A. Kumar, Eds., Singapore: Springer Singapore, 2020, pp. 637–646. Accessed: Aug. 18, 2023. [Online]. Available: http://link.springer.com/10.1007/978-981-13-8618-3_66

[45] Z. Shipstead, T. S. Redick, and R. W. Engle, “Is working memory training effective?,” *Psychological Bulletin*, vol. 138, no. 4, pp. 628–654, 2012, doi: 10.1037/a0027473.

[46] Babette Park, Andreas Korbach, and Roland Brünken, “Do Learner Characteristics Moderate the Seductive-Details-Effect? A Cognitive-Load-Study Using Eye-

Tracking," *Journal of Educational Technology & Society*, vol. 18, no. 4, pp. 24–36, 2015.

[47] A. Bittermann, D. McNamara, B. A. Simonsmeier, and M. Schneider, "The Landscape of Research on Prior Knowledge and Learning: a Bibliometric Analysis," *Educ Psychol Rev*, vol. 35, no. 2, p. 58, Jun. 2023, doi: 10.1007/s10648-023-09775-9.

[48] H. Ebbinghaus, *Memory: A contribution to experimental psychology.* in Memory: A contribution to experimental psychology. Oxford, England: Dover, 1964, p. 123.

[49] H. L. Roediger and A. C. Butler, "The critical role of retrieval practice in long-term retention.," *Trends Cogn Sci*, vol. 15, no. 1, pp. 20–27, Jan. 2011, doi: 10.1016/j.tics.2010.09.003.

[50] M. A. McDaniel, P. K. Agarwal, B. J. Huelser, K. B. McDermott, and H. L. Roediger III, "Test-enhanced learning in a middle school science classroom: The effects of quiz frequency and placement.," *Journal of Educational Psychology*, vol. 103, no. 2, pp. 399–414, 2011, doi: 10.1037/a0021782.

[51] J. Dunlosky, K. A. Rawson, E. J. Marsh, M. J. Nathan, and D. T. Willingham, "Improving Students' Learning With Effective Learning Techniques: Promising Directions From Cognitive and Educational Psychology," *Psychol Sci Public Interest*, vol. 14, no. 1, pp. 4–58, Jan. 2013, doi: 10.1177/1529100612453266.

[52] J. Samani and S. C. Pan, "Interleaved practice enhances memory and problem-solving ability in undergraduate physics," npj Sci. Learn., vol. 6, no. 1, p. 32, Nov. 2021, doi: 10.1038/s41539-021-00110-x

[53] E. Tulving, "Subjective organization and effects of repetition in multi-trial free-recall learning," *Journal of Verbal Learning and Verbal Behavior*, vol. 5, no. 2, pp. 193–197, 1966, doi: https://doi.org/10.1016/S0022-5371(66)80016-6.

[54] B. Finn and I. Henry L. Roediger, "Enhancing Retention Through Reconsolidation: Negative Emotional Arousal Following Retrieval Enhances Later Recall," *Psychological Science*, vol. 22, no. 6, pp. 781–786, 2011, doi: 10.1177/0956797611407932.

[55] D. Davis, R. Kizilcec, C. Hauff, and G.-J. Houben, "Scaling Effective Learning Strategies: Retrieval Practice and Long-Term Knowledge Retention in MOOCs," *Learning Analytics*, vol. 5, no. 3, Nov. 2018, doi: 10.18608/jla.2018.53.3.

[56] D. H. Schunk, "Modeling and Attributional Effects on Children's Achievement: A Self-Efficacy Analysis," vol. 73, no. 1, pp. 93–105, 1981, doi: 10.1037/0022-0663.73.1.93.

[57] R. Azevedo, "Defining and Measuring Engagement and Learning in Science: Conceptual, Theoretical, Methodological, and Analytical Issues," *Educational Psychologist*, vol. 50, no. 1, pp. 84–94, Jan. 2015, doi: 10.1080/00461520.2015.1004069.

[58] J. Padgett, S. Cristancho, L. Lingard, R. Cherry, and F. Haji, "Engagement: what is it good for? The role of learner engagement in healthcare simulation contexts," *Adv in Health Sci Educ*, vol. 24, no. 4, pp. 811–825, Oct. 2019, doi: 10.1007/s10459-018-9865-7.

[59] F. Martin and J. Borup, "Online learner engagement: Conceptual definitions, research themes, and supportive practices," *Educational Psychologist*, vol. 57, no. 3, pp. 162–177, Jul. 2022, doi: 10.1080/00461520.2022.2089147.

[60] Z. Y. Wong and G. A. D. Liem, "Student Engagement: Current State of the Construct, Conceptual Refinement, and Future Research Directions," *Educ Psychol Rev*, vol. 34, no. 1, pp. 107–138, Mar. 2022, doi: 10.1007/s10648-021-09628-3.

[61] X. Ling, J. Yang, J. Liang, H. Zhu, and H. Sun, "A Deep-Learning Based Method for Analysis of Students' Attention in Offline Class," *Electronics*, vol. 11, no. 17, p. 2663, Aug. 2022, doi: 10.3390/electronics11172663.

[62] B. W. Miller, "Using Reading Times and Eye-Movements to Measure Cognitive Engagement," *Educational Psychologist*, vol. 50, no. 1, pp. 31–42, 2015, doi: 10.1080/00461520.2015.1004068.

[63] N. A. Bradbury, "Do I have your attention? Attention and engagement: What are they, and do I want them?," *Advances in Physiology Education*, vol. 47, no. 2, pp. 318–325, Jun. 2023, doi: 10.1152/advan.00022.2023.

[64] I. Calero López and B. Rodríguez-López, "The relevance of transversal competences in vocational education and training: a bibliometric analysis," *Empirical Res Voc Ed Train*, vol. 12, no. 1, p. 12, Dec. 2020, doi: 10.1186/s40461-020-00100-0.

[65] J. García-Álvarez, A. Vázquez-Rodríguez, A. Quiroga-Carrillo, and D. Priegue Caamaño, "Transversal Competencies for Employability in University Graduates: A Systematic Review from the Employers' Perspective," *Education Sciences*, vol. 12, no. 3, p. 204, Mar. 2022, doi: 10.3390/educsci12030204.

[66] C. S. C. Asterhan and B. B. Schwarz, "Argumentation for Learning: Well-Trodden Paths and Unexplored Territories," *Educational Psychologist*, vol. 51, no. 2, pp. 164–187, Apr. 2016, doi: 10.1080/00461520.2016.1155458.

[67] F. Kirschner, F. Paas, and P. A. Kirschner, "Task complexity as a driver for collaborative learning efficiency: The collective working-memory effect," *Applied Cognitive Psychology*, vol. 25, no. 4, pp. 615–624, Jul. 2011, doi: 10.1002/acp.1730.

[68] B. Barron, "When Smart Groups Fail," *Journal of the Learning Sciences*, vol. 12, no. 3, pp. 307–359, Jul. 2003, doi: 10.1207/S15327809JLS1203_1.

[69] J. Janssen and P. A. Kirschner, "Applying collaborative cognitive load theory to computer-supported collaborative learning: towards a research agenda," *Education Tech Research Dev*, vol. 68, no. 2, pp. 783–805, Apr. 2020, doi: 10.1007/s11423-019-09729-5.

[70] D. P. Ausubel, The Psychology of Meaningful Verbal Learning. Grune & Stratton, 1963. [Online]. Available: https://books.google.nl/books?id=ydzRAAAAMAAJ

[71] C. Karachristos and A. Fillipidi, Database schema for augMENTOR, [online]. Available: https://zenodo.org/records/12569236

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Annex I - Meta-review findings

We conducted a meta-review of existing literature reviews on learner modelling published in recent years (2019-2023). We selected six [6] recent publications which we considered relevant [10, 11, 8, 1, 12, and 13] and followed up to synthesizing their findings. Based on this analysis of the state-of-the-art, we formulated the following requirements for the augMENTOR LM.

The recent literature review conducted by Farani et al. [10] noted that only a few LM studies report the use of learning theories, a sentiment echoed by [Bernacki et al. [1] & Abyaa et. al. [13]. Furthermore, various studies investigated by Farani et al. [10] and Bernacki et al., [1] investigated by Farani et al. [10] and Bernacki et al. [1] only vaguely addressed their theoretical foundation by using umbrella keywords, such as "constructivism". Selecting LCs based on learning theories is crucial to learning success [12, 37] but is often only a recommended approach [38]. Farani et al. [10] postulated that the lack of explicit mention of learning theories in LMs may be due to the assumption that learning is a complex process and often constitutes a multitude of theories in any instance. In contrast, Bernacki et al. [1] argued that such assumptions undermine the ability to produce unequivocal evidence of the LM design choices on learner outcomes. Bernacki et al. [1], in their personalization framework termed "Theory of change", propose a top-down approach to select LCs based on theoretical considerations. Selection of LCs based on theory and evidence [13] can simplify – to some extent – the complexity associated with determining which LCs to model. LM designers often face this challenge due to the plethora of LCs available to them [11]. At the same time, Ochukut et al. [11] & Rahman et al. [8] report that the LMs they reviewed often used only a single LC as the basis for personalization, which risks oversimplification of the complex nature of the learning process. For example, recommending students to redo the learning activity based on their grades (LC) without considering the role of other factors, such as prior knowledge (LC), only frustrates them further. Therefore, Ochukut et al. [11] & Rahman et al. [8] advocate for the utilization of more than one LC in making all personalization decisions,

Despite the consensus among researchers advocating theory-driven designs of LMs, there is little evidence to inform the selection of LCs and their respective indicators [8, 11, 10,13]. The lack of a priori conceptualization of an LM based on learning theories limits the investigation of the LCs, which in turn exacerbates this scarcity of evidence [1].

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Annex II - A conceptual overview of the augMENTOR Learner Model

Multi-store Model of Memory

The MuMoMe by Atkinson and Shiffrin [39] provides a cognitive framework to explain the storage of information in long-term memory (see *Figure* below). According to the MuMoMe, human cognition is composed mainly of three groups of memory, namely sensory memory, short-term memory, and long-term memory. In the sensory memory, incoming information from external stimuli is briefly stored. Attended information passes on to the short-term memory, or working memory, when learners engage with it. Consequently, Attention is an essential LCs that must be modelled within the MuMoMe framework. Information in short-term memory can be maintained as long as it is rehearsed and undergoes encoding, a process for storing of information into the long-term memory. The efficacy of the encoding process is influenced by the Prior knowledge of the learner. Information stored in long-term memory is susceptible to Forgetting due to insufficient retrieval-practice. In the following, we elaborate further on how and which LCs, and their corresponding indicators, were selected under the assumptions of MuMoMe and evidence from the literature.

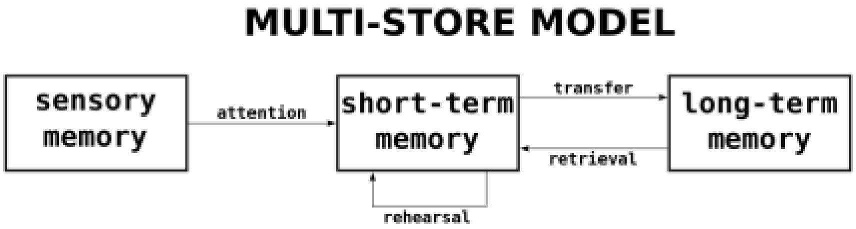

Figure: Multi-store Model of Memory [39]

Learner characteristics in the cognitive domain

Attention

According to the MuMoMe, sensory input from the environment first arrives at the sensory memory. Sensory memory continuously receives new information, but a substantial portion is lost if it is not attended to. Paying attention to the incoming information facilitates the transfer of the information from the sensory memory to the short-term memory. Therefore, attention plays a significant role in the cognitive learning process.

However, prolonged processes such as learning demand “Sustained attention” from learners. Sustained attention refers to the ability to become engaged in and maintain engagement in a task or activity over an extended period of time [41]. The Sustained attention is critical to most everyday tasks with real world implications that impact academic outcomes [42]. To monitor sustained attention in learners, we adopt the sustained attention measurement model from Hwu [16]. This model utilises the Signal Detection Theory, which transforms learners’ responses to learning materials into detectable signals that can indicate their sustained attention. Learners are required to respond to the questions correctly within a predetermined time frame. According to the Signal Detection Theory, sustained attention can be measured in terms of the correctness of the response and the time taken to respond. For example, the delayed response may indicate that the learner is not familiar with the learning material or is not fully focused on the learning activity.

Encoding

Attended information is forwarded to short-term/working memory while the unattended information in the sensory memory is discarded. This incoming information undergoes encoding in the working memory which results in the storage of processed information in the long-term memory. According to the Cognitive Load Theory (CLT) [17], the encoding process imposes "Cognitive Load" (CL) on the working memory, which is limited by the amount of information, and by the duration for which it can hold those information. However, cognitive overload can impede learning, thereby underscoring the importance of monitoring CL in the augMENTOR LM.

Perceived CL is measured in lab-setting with methods such as the dual-task methodology [43] or subjectively with Likert scale responses [44]. We observed, in our meta-review, that the majority of the studies did not model CL as an LC of their LM, except a handful of studies which model working memory capacity [46,47]. While CL and working memory capacity are closely related, there is insufficient evidence to support that working memory capacity is malleable [45]. At the same time, evidence in regards to the non-sensor-based indicators of CL are sparse as most studies measuring CL often tend to use subjective methods [18] such as the single item numerical scale by Paas et al. [19] As this instrument by Paas et al. [19] only contains a single item, it fits within the scope of the project we defined in section 2.1 [Requirements Elicitation]. We will use the Experience Sampling Method, in which the item will be administered every time a learner is engaged in the learning activity. The CL trace generated overtime is more significantly associated with perceived CL by the learners [21].

Prior Knowledge

The most common method of personalization was to provide an adaptive experience based on learners' prior knowledge [1]. Prior Knowledge is considered as one of the most important LC [47] and is a significant indicator of learning [1,22]. Cognitive learning is facilitated when learners possess a meaningful cognitive framework, i.e. prior knowledge, that allows new information to be organized, assimilated, and subsumed in learners' schemata [Subsumption theory, 70]. Furthermore, Prior knowledge also plays a significant role in determining the learners' perceived CL [46].

The method and the granularity of Prior knowledge representation are influenced by the contextual objectives of the LM. However, Bittermann et al. [47] note an increasing use of Item-response theory for prior knowledge elicitation in their review of prior knowledge. A knowledge test can be administered at the start to initialise the learners' Prior Knowledge (as done by Ferreira Da Rocha et al., [23]), after which it is updated based on the students' performance in tests and quizzes.

Retrieval

The information, once stored in the long-term memory, is prone to Forgetting. Ebbinghaus, in what he termed the 'forgetting curve' [48], modelled how information is lost over time from long-term memory unless the learner undergoes retrieval-practice. Therefore, in the long term, it is crucial to monitor if the learners are still able to successfully retrieve specific information from long-term memory. Retrieval-practice can be implemented as a function of learners' performance in tests or quizzes which are quintessential components of every learning experience.

Retrieval-practice, other than to monitor forgetting, also acts as recall re-inforcement [Retrieval-practice effect [49]). Testing inhibits forgetting and improves learning outcomes [50], especially when it is 'spaced' [51] & 'interleaved' [52], in comparison to massed Retrieval-practice done repeatedly within a short time-frame [53]. Spaced-practice, i.e., with progressive delays between practice sessions, and interleaved practice, i.e. alternating topics between practice sessions, impose higher CL but result in deeper processing of information leading to longer retention of information, efficient recall, and transfer of learning [54]. Davis et al., [55] implemented spaced and interleaved retrieval-practice via testing, based on the learners' prior knowledge and learning trace, in which a suitable test item was selected from a list of test items.

These four aforementioned LCs derived from the MuMoMe together enable the augMENTOR LM to monitor cognitive learning and provide actionable insights. For example, in the event of the failure to perform satisfactorily in the test administered immediately after exposure to the learning activity, the augMENTOR LM allows insights into the learners' prior knowledge or the CL experienced for further investigation. Additionally, rather than merely monitoring the learner, the LM also prompts the learner to engage in the learning activity. This is useful to monitor and foster learning beyond the initial exposure to the learning activity.

Learner characteristics in the affective domain

Fariani et al., [10] recommended emphasising the affective domain in LMs after they found no studies discussing affective aspects, such as emotions and motivation, in their review. The affective domain of learning emphasises the role of emotional engagement in shaping cognitive processes. A multitude of researchers acknowledges that emotions directly affect memory [24, 25, 26]. Similarly, other affective factors such as motivation and engagement have been regarded as some of the strongest predictors of learning [27, 28]. Therefore, the augMENTOR LM also boasts an affective dimension in its core LM design.

Motivation and Engagement

We emphasise the affective domain in augMENTOR by modeling "Motivation" and "Engagement" in our LM. Motivation is the process whereby goal-directed activities are instigated and sustained [56] and has been found to be a major driver of engagement in learning [29]. Motivated and engaged learners achieve superior learning [30]. Although, the consensus on the importance of engagement for learning has been well established, researchers have yet to agree on the different dimensions of Engagement [57, 58, 59]. This is evident in the ambiguity in the literature regarding the operationalisation of Engagement [60] and the difficulty of measuring it [61].

The "Engage Taxonomy" by Cristea et al., [31] provides metrics for measurable engagement in MOOCs based on the "Self-determination theory (SDT)" [32]. Therefore, it is well suited for our objectives in augMENTOR to account for modeling of both affective and social factors, as the SDT studies motivation at a social level. The Enagage Taxonomy assumes that satisfying the three innate psychological needs, i.e. Autonomy, Relatedness and Competence, promotes motivation which inturn promotes engagement with the learning activity. Competence reflects the desire to engage with the learning environment to experience mastery. Autonomy pertains to the need to feel in control of one's own behaviors and goals, while relatedness refers to the sense of belonging to a community and connectedness to others. The Engage Taxomony provides specific measures for these three psychological needs which are useful for generating actionable insights. The Engage Taxonomy also provides validated selection of evidence-based indicators for each psychological needs, along with the methods to quantify them.

Additionally, Attention and Engagement are thought to influence each other. Miller [62] highlights the importance of attention by defining it as "the baseline of engagement". While the nature of the relationship between Attention and Engagement is still under investigation, it is generally accepted that Attention constitutes a part of Engagement. Bradbury [63] distinguishes the two concepts by stating, "if you have your students' Attention, you can pour information into them; but if you have their Engagement, they are actively craving content from you".

Transversal skills

Transversal skills, or soft skills, are non-technical skills that overlap, or transverse, application domains and are often related to an individual's ability rather than the possessed knowledge. In their review findings, Calero López and Rodríguez-López [64] observed the need to improve learners' transversal competencies to meet the demands of the labour market. Similarly, García-Álvarez et al., (65) found that employers placed high importance on Job-related basic skills such as communication and socio-relational Skills such as collaboration.

In the context of the augMENTOR LM, we propose the modeling of transversal skill - and in particular, Collaboration, Critical Thinking and Creativity - separately than cognitive and affective aspects, mapping the pedagogical strategy of the project that is designed in WP3 ("Pedagogical Framework for Emerging Technologies") and WP4("Critical Thinking and Creativity"). As established in WP4, transversal skills like the ones we address in augMENTOR, are measured mainly with the use of rubrics while there is a lack of validated frameworks that relate data-driven approaches to the assessment of Critical Thinking and Creativity. Indeed, extensive work is carried out regarding the automatic assessment of Collaboration [33,34] - as part of research in the area of Computer-Supported Collaborative Learning (CSCL) - but these works do not explicitly relate collaboration with the cognitive or affective domains of learning.

Abyaa et al. [13] underscore the various importance of modeling collaboration in determining learning outcomes. However, Asterhan and Schwartz [66] argue that "positive interdependence" is a prerequisite for effective and efficient collaborative learning. Positive interdependence exists when the input and effort of all group members are required to complete the collaborative learning task. Once positive interdependence is manifested in the learning tasks, individual learners strive to acquire "Transactive knowledge", which is a shared understanding and an awareness of which group member possesses what knowledge and expertise [67]. The transactive knowledge is crucial for the collaborative "transactions" required in the orchestration of collaborative learning tasks. In augMENTOR LM, we model the process of collaboration by analysing the collaborative transactive discourse. Barron [68] showed that learners who actively linked their ideas and contributions to what others had previously said in transactive discussions learned better.

In addition, we also analyse the individuals' CL when they are engaged in collaborative learning tasks. The theory of "Collaborative Cognitive Load Theory (CCLT)" [69] provides a framework to investigate collaborative learning under the notion of positive interdependence. CCLT assumes that Cl is shared in a group due to the collective working memory, which assumes that individual learners pool their working memory capacity together to solve much more complex tasks. In addition, individual learners do not need to possess all the necessary prior knowledge individually and also do not need to complete the tasks all by themselves. Therefore, measures of CL can provide insights into the nature of collaboration and act as a point of reference to corroborate the insights obtained from the transactive discussions.

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