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Electronic, didactic and innovative platform for learning based on multimedia assets

e-DIPLOMA

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D.5.1 Competency Specifications: Theoretical explanation

Version No.V1.2

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1. Introduction

1.1 Executive Summary

Learning involves acquiring new knowledge, skills, behaviours, or attitudes through study, experience, or teaching. It is essential for human development and occurs throughout life in various contexts. Students learn most effectively through experimentation, practice, and experiential learning. This deliverable aims to explain the process of experiential learning and the cognitive skills required for acquiring new knowledge. It also provides a theoretical framework for analysing learning facilitated by disruptive technologies. This analysis should aim to answer the following question: Do disruptive technologies improve the learning process? This question is formalised in accordance with the cognitive and affective model (CAMIL), which proposes a theoretical basis for learning with new immersive technologies, considering the cognitive and affective skills (cognitive load, self-regulation, interest, embodiment, self-efficacy and motivation). Hence, in this deliverable, cognitive load, self-regulation, interest, embodiment, self-efficacy and motivation are defined and measured as an implicit part of learning. These cognitive and affective skills are going to be measured indirectly by collecting behavioural and psychophysiological measures (eye tracking, electrodermal activity and heart rate variability) which are theoretically explained and linked to the cognitive and affective skills selected.

1.2 Relation to Other Project Documents

This document is related to Deliverable 5.2. While this document describes the theoretical considerations on how competencies can be modelled and what models are relevant to the e-DIPLOMA project, Deliverable 5.2 lays out the exact methods and protocols to be pursued.

1.3 Abbreviation List

Among the acronyms more used in the present document are the following:

VR: Virtual Reality

AR: Augmented Reality

XR: Extended reality

AI: Artificial Intelligence

CAMIL: Cognitive and Affective Model of Immersive Learning

HR: Heart Rate

ET: Eye Tracking

EDA: Electrodermal activity

CL: Cognitive Load

SRL: Self-regulated Learning

1.4 Reference Documents

See References Section included in this document.

2. e-learning ecosystem for practice-based learning with disruptive technologies

This deliverable explores learning and the cognitive skills that interact during the acquisition of new knowledge in e-learning. We understand e-learning as the method of delivering educational content and facilitating learning through digital platforms and technologies.

The current deliverable aims to explain the process of e-learning, as well as the cognitive skills involved in the acquisition of new knowledge, this deliverable gives a theoretical context of the methodology to be used during the analysis of learning mediated by disruptive technologies. Firstly, a theoretical conceptualisation of the learning model and cognitive and affective skills is explained. Secondly, the psychophysiological and behavioural measures that will be employed to investigate learning acquisition are explained. Lastly, the relationship between the skills and the psychophysiological measures is clarified.

The main research question of this deliverable is:

RQ. Are disruptive technologies enhancing learning?

Three particular sub-questions were formulated for the literature review analysis:

RQ 1: Which technologies are considered most useful in the literature?

RQ 2: What mechanisms are considered in the literature to model the effect of learning contexts or types of content?

RQ 3: What does the literature say about how cognitive and emotional skills are most useful to enhance the learning mediated by technologies?

All these issues are resolved through a theoretical approach in this deliverable, which is proposed as a theoretical background to the methodological design in deliverable 5.2.

In this deliverable, we aim to provide a theoretical justification for the research and proposed methodology, in which we elucidate the theoretical underpinnings of the disruptive technologies employed in the project and their efficacy in the learning process. This is based on the premise that these concepts are adapted to experiential learning paradigms, in which individuals assimilate new concepts through direct interaction with emerging technologies.

2.1 State of Art of Practice-Based Learning

Learning is the process of acquiring new knowledge, skills, behaviours, or attitudes through study, experience, or teaching. It is a fundamental aspect of human development and growth, occurring throughout our lives in various forms and contexts. To engage, motivate, and teach at optimal levels, we must understand the learning process in general (Kacetl, J., & Semradova, I. 2020).

The outcome of the learning processes depends on the availability of required knowledge (declarative and procedural knowledge) as well as on the goal set, on the proper sequencing (i.e., planning) of the procedures to be applied for reaching the goal, on the monitoring and control of cognitive processing, and the evaluation of whether the processing outcome satisfies or does not satisfy the goal- and performance-criteria set.

Emerging technologies have promoted a move towards an experiential learning model that emphasises the value of hands-on practice and practical application. This method proposes that people learn best through active involvement in tasks and experiences, as opposed to passive information absorption (Yao, 2023). The hypothesis asserts that by actively participating and experimenting, individuals gain a more profound comprehension of concepts, while also improving their problem-solving skills, critical thinking, and practical knowledge (Zajda, J. 2021).

These abilities are essential for successful application in real-life scenarios. Learning by doing is often associated with experiential learning theories, which propose that learners acquire knowledge and skills through reflection on their experiences. This method is commonly used in various educational settings, such as vocational training, apprenticeships, and project-based learning environments (Anzai & Simon, 1979; Thompson, 2010).

According to Kolb's theory (2009), learning is a cognitive process that involves continuous adaptation and interaction with one's environment. Individuals generate knowledge through their experiences rather than solely from traditional instruction. The multi-perspectival and adaptive aspects of Kolb's Experiential Learning Theory (KELT) highlight different learning styles and stages within a learning process rather than a means of allocating particular learning styles to specific students (Kolb & Kolb, 2009).

In conclusion, this theory summarises how students learn best through experimentation, practice and experiential learning. Thus, experiential learning happens through interaction with the environment and this interaction is dynamic and often incorporates collaborative activities, discussions and technology to facilitate active participation. This method emphasises direct involvement and interaction, allowing learners to engage deeply with content, apply knowledge in real-time and develop critical thinking and problem-solving skills through continuous feedback and interaction.

To facilitate learning based on experimentation, the use of disruptive technologies is proposed as an effective methodology. Disruptive technologies in learning are innovations that transform traditional educational methods and environments. These technologies often introduce more efficient, accessible, or personalised learning experiences, challenging and potentially replacing conventional practices. Examples include online learning platforms, artificial intelligence-driven tutoring systems, and virtual or augmented reality applications, all of which have the potential to reshape how education is delivered and received. (Turan, Z., Karabey, S.C., 2023)

2.2 Learning with Disruptive Technologies

At this point, a theoretical approach is given in response to questions 1 and 2 (RQ1 and RQ2), for which it is first necessary to understand what disruptive technologies are and what types of technology they include.

Disruptive technologies are innovations that significantly alter or replace existing technologies, industries, or markets. They typically introduce new processes, products, or services that eventually transform the way businesses and societies operate. The integration of these disruptive technologies in learning and education could enhance the effectiveness, accessibility, and personalisation of the learning experience. By leveraging these advancements, educators can create more engaging and impactful educational environments that cater to the diverse needs of learners. There are various types of disruptive technologies (AI, machine learning, AR, VR, 3D printing…). Here, some of the most commonly used ones are explained, such as immersive technologies (VR), augmented reality, artificial intelligence, and programs like Edison (Sandoval-Henríquez, F.J., Sáez-Delgado, F. & Badilla-Quintana, M.G. 2024)

Virtual reality (VR) is an immersive and disruptive technology that delivers realistic experience or presents a realistic environment through computer-generated simulations. Users can interact with and explore these virtual worlds in three dimensions, often through specialised VR headsets. VR technology aims to create a sense of presence, allowing users to feel as though they are physically located within the virtual environment. It has applications across various industries, including gaming, entertainment, education, healthcare, training, and simulation. VR experiences can range from simple immersive environments to complex simulations that replicate real-world scenarios with high fidelity (Lindner, P. 2021).

Meanwhile, augmented reality (AR) is a technology that overlays digital information or virtual objects onto the real world, typically viewed through a smartphone, tablet, or wearable device like smart glasses. Unlike virtual reality, which immerses users in entirely virtual environments, AR enhances the physical world by superimposing digital elements onto it. These digital overlays can include text, images, videos, 3D models, or animations, seamlessly integrated with the user´s environment and accurately placed virtual content (Jang, J., et al,.2021).

Some researchers, such as Osadchyi et al. (2020) and Checa & Bustillo (2020), identify several VR capabilities, such as immersion in the simulated environment, multimodal interaction, concretisation of imagination, embodiment, and empathy for users. Studying the impact of VR and AR technology on education, Faridi et al. (2021) have revealed various benefits related to knowledge acquisition, commitment, motivation, and academic performance. This alternative educational approach has an additional value due to the high accuracy in representing three-dimensional virtual objects and the opportunity for students to model operations and procedures of abstract concepts. Learning with immersive and disruptive technologies improves the memorisation of complex or abstract topics based on intangible concepts. Such an experience increases motivation and engagement improvements, as well as obtaining emotional satisfaction.

Therefore, there is a need to find a methodology for effective learning, but the characteristics of the student cannot be underestimated, as it is the student who has to acquire the new content shown. The student has some basic cognitive characteristics that allow them to process the learning of new content. The variability in these characteristics can be a determinant for the acquisition of knowledge, as explained by the immersive learning model.

In the next paragraphs, the Cognitive and affective model of immersive learning (CAMIL) is going to be explained, this model explains at a theoretical level how some cognitive and affective skills modulate learning.

2.3 The cognitive and affective model of immersive learning (CAMIL)

This model is proposed to give a theoretical approach to the third and last question (RQ3), which is the need to understand how and what influences learning.

The cognitive and affective model of immersive technologies (CAMIL) (Makransky & Petersen, 2021) refers to a framework for understanding how virtual reality (VR), augmented reality (AR), and other immersive technologies impact both cognitive processes (such as perception, attention, memory, and decision-making) and affective responses (emotions, attitudes, and behaviours) of users.

In this model, cognitive processes are influenced by the immersive nature of the technology, which can enhance perception by providing realistic sensory experiences, manipulate attention through immersive stimuli, affect memory by creating vivid and memorable experiences, and impact decision-making by simulating real-world scenarios.

In immersive learning environments like VR and AR, affective responses play a significant role in influencing users' engagement and learning outcomes. The Cognitive Affective Model of Immersive Learning (CAMIL) acknowledges the importance of traditional learning theories while highlighting the unique affordances of XR, particularly presence and agency. CAMIL identifies six key factors—interest, intrinsic motivation, self-efficacy, embodiment, cognitive load, and self-regulation—that contribute to knowledge acquisition and transfer in immersive environments.

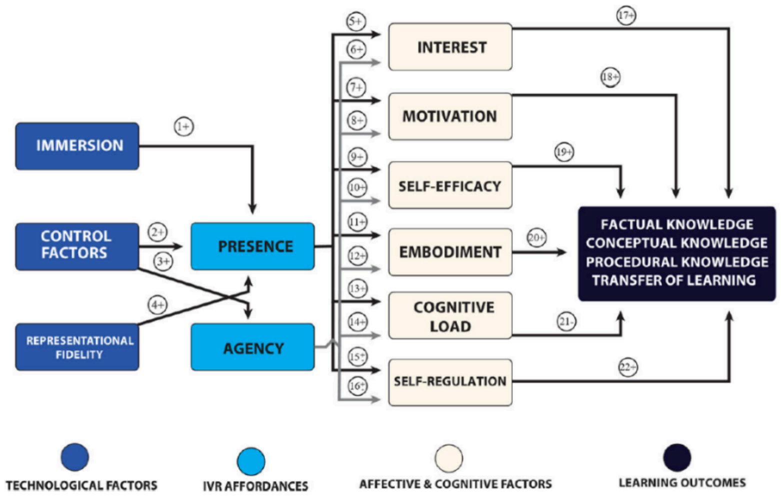

Figure 1 (Makransky & Petersen, 2021)

In summary, the general theoretical framework of the model presupposes that motivational and learning strategies, which have been validated through research using less immersive media, apply to extended reality (XR) learning environments. Nonetheless, the Cognitive Affective Model of Immersive Learning (CAMIL) emphasises that the interaction between media and methods plays a crucial role. CAMIL outlines six cognitive and affective factors that influence learning outcomes (see Figure 1). Having contextualised and explained the model, the six cognitive and affective characteristics will now be detailed (Makransky & Petersen, 2021).

2.3.1 Cognitive and affective skills that modulate learning

2.3.1.1 Situational interest

Interest is a multifaceted psychological construct representing the connection between an individual and a specific topic, blending affective and cognitive elements. Research consistently demonstrates that interest profoundly influences learning outcomes. It manifests as a psychological state that not only predisposes individuals to engage with content but also persists across various learning contexts and age groups. For instance, imagine someone in a waiting room engrossed in an article from a magazine on an unfamiliar topic. Here, their interest is spontaneously sparked by the situation itself, termed situational interest, which inherently motivates them. This type of interest can be triggered by external stimuli, such as the presence of the magazine. Furthermore, if the individual perceives the article as relevant to a subject they have been curious about and experiences a surge of excitement, it signifies a personal interest in that topic (Hidi & Ann Renninger, 2006).

The development of interest is addressed by the *Four phase mode of interest* (Hidi & Ann Renninger, 2006), which suggests that the phase of a person's interest might predict the particulars of cognitive evaluation and that the process of interest engagement would not necessarily be one of which the person was wholly metacognitively aware. People may make a decision to become interested in particular content, but, more typically, interest mediates how they engage content and impacts whether and how they choose to reengage that content over time. As interest progresses, individuals begin to pose curiosity-driven questions, prompting them to seek repeated involvement and accumulate both positive emotions and enhanced knowledge and value associated with specific content. The contrast between an emerging and a fully developed interest lies in self-regulated actions, such as actively seeking answers to curiosity-driven inquiries. Those with well-developed interests exhibit independent pursuit of deeper understanding and actively learn from feedback. Additionally, they tend to uphold positive sentiments towards the content and demonstrate persistence in overcoming challenges or setbacks (Harackiewicz &. Smith, 2016). This model is characterised by four phases where both types of interest are developed. The four phases are (1) triggered situational interest, which refers to a psychological state of interest, (2) maintained situational interest which involves focused attention and persistence over an extended period, (3) emerging individual interest, which refers to a relatively enduring predisposition to seek repeated re-engagement, (4) well developed individual interest, refers to a physiological state of interest to a relatively enduring predisposition over the time (Fives, H., & Dinsmore, 2017).

Hence, interest is a predisposition to reengage content that applies to in-school and out-of-school learning and young and old alike. Taking this into account interest includes a curiosity state and attentional process (Makransky & Petersen, 2021).

Curiosity serves as an intrinsic motivator that compels individuals to explore, discover, and seek new information and experiences. It may manifest as an eagerness to acquire knowledge about a specific topic, a persistent questioning attitude, or a propensity to engage in novel activities and solve problems. (Jirout et al., 2022).

In the context of learning, attention refers to the cognitive process by which learners selectively concentrate on specific information or tasks, thereby improving their ability to perceive, process, and retain that information. This process involves allocating mental resources to pertinent stimuli while filtering out distractions, thus facilitating more effective learning and comprehension. Attention is a crucial factor in academic performance, as it directly impacts the acquisition and integration of new knowledge and skills. (Eldar, E., Cohen, J. D., & Niv, Y. 2013).

2.3.1.2 Self-efficacy

Self-efficacy pertains to individuals' confidence in their ability to manage challenging tasks and their overall functioning. It is considered a context-specific concept that is responsive to nuanced changes in a student's performance and interacts with self-regulated learning processes, thereby influencing academic achievement (Bandura, 2006). This construct represents a positive self-belief, reflecting the conviction that one can successfully undertake new or difficult tasks and handle adversity across various aspects of human activity. (Moos, 2014).

Self-efficacy is a key construct that influences subsequent behaviour, making it highly relevant for both professional and academic practices as well as for behaviour modification. It can facilitate behavioural changes and support optimal performance (Schwarzer & Luszczynska, 2008). Additionally, human functioning is influenced by beliefs regarding the malleability of ability. Individuals who perceive ability as a skill that can be developed and honed tend to achieve higher accomplishments. Increased cognitive effort, in turn, enhances memory performance. Perceived cognitive self-efficacy impacts memory performance both directly and indirectly by boosting cognitive effort (Bandura, 1993).

In connection with this topic, Moos (2014) conducted a study linking self-efficacy to metacognitive processes. Individuals with high self-efficacy in learning tasks typically exhibit heightened levels of metacognitive monitoring, assessing both their comprehension of task content and the significance of learning materials.

Therefore, self-efficacy correlates directly with self-regulation, which is not merely a mental capacity or an academic aptitude but rather the self-guided mechanism through which learners translate their mental capabilities into academic competencies (Winne, 2015; Zimmerman, 2000). Self-regulated learning (SRL) (Bernacki et al., 2015) includes the cognitive, metacognitive, behavioural, motivational, and emotional/affective aspects of learning. The existence of variation in self-efficacy supports the assumption that self-efficacy changes over a learning task, potentially in response to other SRL processes.

2.3.1.3. Cognitive load

Cognitive load pertains to the mental exertion necessary for processing information or executing a task, encompassing the number of cognitive resources, such as attention and working memory, required to manage the demands of a specific activity (De Jong, T. 2010).

The cognitive load theory presents a significant framework that categorises the allocation of cognitive resources during explicit learning into three distinct types: extraneous, intrinsic, and germane. This theory, developed by educational psychologist John Sweller (2011), identifies cognitive overload as stemming from an excessive demand for cognitive resources, particularly working memory capacity. There are three types of cognitive load:

1. **Intrinsic Cognitive Load:** This refers to the inherent challenge of the material being studied or the task being undertaken. It is influenced by the complexity of the subject matter and the learner's current knowledge and skills in that area. Intrinsic cognitive load is not directly modifiable through instructional design but can be effectively managed by breaking down complex information into smaller, more manageable segments.
2. **Extraneous Cognitive Load:** This pertains to the mental effort required due to how instructional content or materials are designed or presented, which does not directly aid learning. Extraneous cognitive load arises from poorly structured instructional materials, confusing formats, irrelevant information, or distracting elements. Effective instructional design strives to reduce extraneous cognitive load to enhance learning outcomes.
3. **Germane Cognitive Load:** This denotes the cognitive effort required to process and incorporate new information into existing knowledge structures or schemas. It is linked to meaningful learning and the formation of mental models. Unlike intrinsic and extraneous cognitive load, germane cognitive load is seen as advantageous for learning, as it signifies the cognitive investment in comprehending and elaborating upon new information.

Cognitive load theory (Paas & Sweller, 2012) examines how cognitive resources are directed and utilised during learning and problem-solving. Many instructional methods and problem-solving approaches encourage students to engage in cognitive tasks that diverge significantly from the intended objectives of the task. The cognitive load imposed by these irrelevant activities can hinder the acquisition of skills. This theory has been instrumental in developing various instructional strategies, which rely heavily on the principle of borrowing and reorganising. These strategies primarily focus on presenting information to learners in ways that facilitate the acquisition of schemas. In addition to schema acquisition, cognitive load theory also addresses automating these schemas so that they can be used without conscious processing in working memory.

According to cognitive load theory, short-term or working memory has a limited capacity and can effectively handle only a restricted amount of information at once. When working memory becomes overloaded, individuals may struggle to process information adequately, leading to potential difficulties in understanding, retention, and learning (Mestre, 2012). The extent of cognitive load correlates with the quantity and quality of learning acquisition; the effective utilisation of working memory is crucial for acquiring new knowledge.

2.3.1.4 Motivation

Motivation is a theoretical concept which refers to the internal processes that energise, direct, and sustain behaviour toward achieving a goal. Therefore, motivation is an attribute that instigates movements, energy, direction, the reason for our behaviour, and "what" and "why" we do something. Motivation has been related to the amount of intellectual energy typically used in learning activities, and this led to a belief that motivation could be seen as a stable characteristic of the individual, on a par with personality (Filgona et al., 2020).

Other researchers have contributed to this discussion. Spolsky (2000) defined motivation as the time a learner is willing to dedicate to learning tasks. He proposed that motivation is an individual's readiness to engage in a task, influenced by both personal factors and external circumstances. Similarly, Filgona et al. (2020) characterised motivation as the drive or effort directed towards a specific goal, contrasting with a previous lack of interest or attraction towards that goal.

Self-determination theory (SDT) (Ryan, R. M., & Vansteenkiste, M. 2023) provides a comprehensive framework for understanding the factors that support or diminish intrinsic motivation, autonomous extrinsic motivation, and psychological well-being, particularly within educational contexts. The theory distinguishes between two types of motivation: intrinsic and extrinsic. Intrinsic motivation involves engaging in an activity or pursuing a goal because of the inherent satisfaction, enjoyment, or interest it brings rather than solely for external rewards or pressures. It is driven by internal factors such as curiosity, autonomy, mastery, and personal fulfilment. Individuals with intrinsic motivation are motivated by the inherent satisfactions of the activity itself rather than by external outcomes. Unlike extrinsic motivation, which involves seeking rewards or avoiding punishment, intrinsic motivation derives from the inherent enjoyment and fulfilment of the task. While intrinsic motivation is inherent to individuals in one sense, it also depends on the relationship between individuals and specific activities. People may be motivated intrinsically for some activities but not others, and not everyone is intrinsically motivated for any given task (Ryan, R. M., & Deci, E. L. 2020).

The concept of motivation was initially recognised through experimental studies of animal behaviour, revealing that many organisms exhibit exploratory, playful, and curiosity-driven behaviours even without reinforcement or reward (David & Weinstein, 2023).

2.3.1.5. Emotional self-regulation

Emotional self-regulation, involving the understanding, acceptance, and control of emotional responses, is a process undertaken by individuals to adapt to their psychosocial environment and advance towards their developmental goals, thereby promoting mental well-being (Van Lissa et al., 2019). Attaining emotional self-regulation fosters greater autonomy and correlates with the development of healthy self-esteem and feelings of self-efficacy, which facilitate social and academic adjustment (Alarcón-Espinoza et al., 2022). In contemporary psychology, the study of emotion regulation intersects with research on attachment (Bowlby, 1979), as well as self-regulation (Makransky & Petersen, 2021), among other related topics.

Recent studies on emotions have delineated them as multifaceted processes encompassing distinct affective, cognitive, psychological, and behavioural components (Mega et al., 2014). The attainment and management of emotions wield a substantial influence on students' academic achievements. Several mediating factors contribute to these effects, such as cognitive resources, learning strategies, self-regulated learning, and motivation to learn. Consequently, emotions can either enhance or diminish the application of diverse learning strategies and promote distinct forms of regulation, such as self-regulation versus externally regulated learning. Moreover, emotions significantly impact students' intrinsic motivation to engage in learning activities (Wu, R., & Yu, Z. 2022).

2.3.1.6 Embodiment

Embodiment refers to the idea that cognitive processes, emotions, and experiences are rooted in the physical body and its interactions with the environment. This concept posits that our perception, understanding, and even consciousness are influenced by sensory-motor interactions and bodily experiences. In essence, the body does not merely serve as a container for the mind but actively shapes and limits our thoughts, emotions, and behaviours. Theories of embodiment suggest that cognition is fundamentally embodied, emphasising that bodily sensations and experiences are pivotal in shaping our mental processes and subjective experiences (Leung, A. K. Y., Qiu, L., Ong, L., & Tam, K. P. 2011).

The embodied view of cognition is based on sensory and motor experiences (Maye & Engel, 2013; Mahon, 2015), which generate multimodal sensorimotor representations in the brain. From a purely mechanistic perspective, cognition emerges as a result of brain functions within a highly interconnected network of cells. These cells respond to external stimuli received through sensory organs such as the ears, eyes, skin, nose, tongue, and motor actions involving other body organs. Therefore, the "mind" or "reason" is performed by the brain, which is an integral organ of the body. This perspective shifts away from viewing the mind as an abstract entity (Macedonia, 2019).

In emerging technologies like virtual reality (VR) or augmented reality (AR), embodiment describes the experience of feeling present and interacting within a virtual environment through an avatar or virtual body. This embodiment perception includes two sensations, which are the sense of presence, understood as the sense of being there (inside of the virtual environment), and the sense of agency, which includes the sense of being in control of what the participant does in the virtual environment. It entails the perception that the virtual body represents oneself, fostering a feeling of ownership and control. Achieving embodiment in VR/AR relies on sensory cues like visual, auditory, and haptic feedback, which collectively create a convincing illusion of inhabiting the virtual body. This sensation of embodiment enhances immersion and presence in the virtual environment, resulting in more realistic and engaging experiences.

The theories of embodied cognition suggest a connection between motor and visual processes; the more explicit the connection, the better the learning, which suggests that embodiment is important for learning (Makransky & Petersen, 2021). Evidence suggests that when a motoric modality is added to the learning experience, more neural pathways are activated, which results in more learning or memory traces (Johnson-Glenberg, 2018). Furthermore, there is evidence that learning increases when a particular concept's bodily interactions and visual features are coordinated.

In summary, these are the cognitive and affective skills involved in learning, which collectively interact with the content and methodology presented, leading to more or less effective learning. These skills can be measured by questionnaires and self-reports, which are the traditional measures used to assess cognitive, personality, attachment and other characteristics. These metrics are effective but have some limitations due to the need for active user participation. For example, individuals are not always accurate in their self-assessment, and their answers may be influenced by factors such as social desirability bias or response style. From the standpoint of ecological validity, they are decontextualised measures of real situations and do not elicit the same behavioural responses as in real life.

Another way to collect values of these cognitive and affective characteristics is through the use of implicit measures, which are techniques used to evaluate mental and emotional processes that occur automatically and unconsciously. Unlike explicit measures, such as questionnaires and self-reports, which require the active and conscious participation of individuals, implicit measures aim to capture more natural responses that are less susceptible to manipulation or conscious bias.

For the methodology of this project, the use of implicit measures, such as psychophysiological and behavioural measures, is chosen, as they are less susceptible to manipulation or conscious bias. Additionally, these measures allow us to assess what happens to the individual while they engage in other cognitive processes, such as learning new knowledge. In the following sections, the chosen psychophysiological and behavioural measures are specified and explained from a theoretical perspective, and each skill is linked to a different psychophysiological measure.

3. Physiological measurement metrics

This section outlines the psychophysiological and behavioural measures that will be employed to investigate learning. These measures will be gathered in both disruptive and non-disruptive environments across prototypes one, two, and three. It provides an explanation and theoretical justification for their use in these prototypes. To answer question 3 (RQ3), the measurement of the different cognitive abilities employing psychophysiological measures is proposed. Subsequently, the methods for collecting these measures and linking them with each specific metric will be detailed in Deliverable 5.2.

Psychophysiological measures analyse how psychological and physical states interact, employing various instruments in laboratory and real-world environments. Enhanced by modern tools for assessing the brain and central nervous system, these measures have significantly deepened our comprehension of how these systems interact and their impact on behavioural processes and emotions. (Lohani et al., 2019).

Psychophysiological measures provide distinct advantages, such as the capability to gather continuous data linking physiological responses with concurrent stimulus presentation effects. Moreover, psychophysiology can reveal phenomena that are difficult to capture using conventional self-report techniques, offering a more precise analysis of an individual's physiological state compared to self-reporting or observable behaviour (Caruelle et al., 2019). An emotional experience does not simply consist of the description one can make of this experience (Lane, R. D., & Smith, R. 2021). Apart from the subjective part, the experience also consists of behavioural responses and physiological changes (Bradley, M. & Lang, 2000; Gross, 1998; Kring & Gordon, 1998). Physiological changes are crucial in distinguishing affect from cognition. Emotions begin with physiological experiences, such as increased heart rate or sweating. It's only after the mind perceives these physiological changes that individuals become aware of their emotions (Lazarus, 1991).

3.1 Electrodermal activity

Electrodermal Activity (EDA), also called galvanic skin response (GSR), skin resistance, and skin conductance, EDA refers to the electrical activity of the skin. Importantly, EDA is a good non-invasive measure of moment-to-moment changes in SNS activation (Posada-Quintero & Chon, 2020). EDA relies upon eccrine gland activation, which is the major sweat glands found throughout the human body in the skin. These glands are especially densely distributed in the hands and feet. Increased SNS activity activates the eccrine glands to produce sweat. Importantly, EDA measures eccrine activity regardless of whether sweat is produced (Gaffey, A.E., Wirth, 2014).

While changes in electrical activity alone do not pinpoint specific emotions, they do correlate with emotional arousal—indicating the user's level of alertness or relaxation (Horvers, A., et al., 2021). Skin conductance devices detect Electrodermal Activity (EDA) by measuring skin conductance. This measurement assesses the electrical resistance between two electrodes, typically placed about one or two centimetres apart on the skin, while a slight current flows continuously between them. (Braithwaite et al., 2013, Tseng et al., 2022).

3.2 Heart rate variability

Heart rate variability (HRV) is defined as changes in the time intervals between consecutive heartbeats. These changes are expected to occur and reflect autonomic nervous system (ANS) activity (Pham et al., 2021). An optimal level of HRV is associated with health and self-regulatory capacity, as well as adaptability or resilience. Higher levels of resting vagal HRV are related to the performance of executive functions such as attention and emotional processing by the prefrontal cortex. Processing of afferent information by the intrinsic cardiac nervous system may modulate front cortical activity and impact higher-level functions.

Heart rate can be measured using several techniques, each with its advantages and specific applications. Measuring the heart rate could be done by Electrocardiogram (ECG) or by photoplethysmograph (PPG). These techniques are complementary techniques for assessing cardiovascular function. The ECG measures the electrical activity of the heart through electrodes on the skin, providing detailed data on cardiac depolarisation and repolarisation. In contrast, PPG measures changes in blood volume in tissues by absorbing light, providing information on heart rate and oxygen saturation, and is commonly used in wearable devices for continuous health monitoring (Zhang et al.,2024).

Photoplethysmography (PPG) is a non-invasive method for measuring blood volume changes in a microvascular bed of the skin based on optical properties of PPG methodology, such as absorption, scattering, and transmission properties of the human body composition under a specific wavelength of light (Castaneda D, Esparza A, Ghamari M, Soltanpur C, 2018). At its heart, the PPG technology is remarkably simple, consisting of a light source on one side of the tissue bed and a light detector on the other. Holding one hand in front of a bright light and looking at the red glow creates a PPG in its simplest and most accessible form. PPG records the amount of light transmitted or reflected by the change in concentration of substances in the blood and the optical path according to the pulsation (Alian & Shelley, 2014).

4. Behavioural metrics

These two sections (points 3 and 4) explain the psychophysiological and behavioural measures that will be used to investigate learning, all of which will be collected during disruptive and non-disruptive environments (prototypes one, two and three). This is an explanation and theoretical justification of their use in the prototypes; later, their collection and linkage with each of the metrics will be defined (Deliverable 5.2).

4.1 Eye-tracking

Eye-tracking is a sensor technology that measures and records the position and movement of the eyes. An eye tracker is a device for assessing where or what one is looking at, also known as *the point of gaze* (Mele & Federici, 2012).

The point of gaze can be identified across various types of stimuli. Typically, an individual whose eyes are tracked directs their attention to a stimulus that may appear on a computer screen, in a real-world environment, or in a virtual reality. It works by identifying the location to which gaze is directed (point of regard) independently of movements of the head or the eye-tracking device, real-time calculations on reflections visible on the cornea (the transparent cover of the front of the eye), and the centre of the pupil are necessary (Rahal & Fiedler, 2019). Eye trackers can be used as standalone devices or be integrated into other technology, such as XR headsets, PCs, and vehicles.

This eye-tracking is understood as a versatile research method that circumvents these measurement problems by unobtrusively recording the information search and integration process as well as changes in the individual's affective state. It does so without interrupting the process itself and provides a direct measure of the information acquisition and weighting occurring before a choice is made or an action is initiated (Rahal & Fiedler, 2019).

Eye-tracking technology has a broad range of applications, including scientific and medical research, accessibility for people with disabilities, improving road safety in driving, and enhancing virtual reality and gaming experiences. In summary, ET is a non-invasive method for measuring visual attention, offering researchers extensive insights into how people process information. By recording eye movements, researchers can identify attention patterns, such as what people look at first, how long they focus on different areas, and how their attention is influenced by various stimuli (De-Juan-Ripoll et al., 2021).

4.2 Decision making during the experience

Technologies such as VR/AR or computer games allow us to measure the user's behaviour in a very fine-grained manner, or in other words, to trace the user's behaviour. To assess behaviour within a field experiment, the typical approach is to code elements of the social interaction of interest in real-time or via recordings. Processing and coding such interactions for verbal and especially nonverbal content are time-consuming and resource-intensive (Yaremych & Persky, 2019).

In virtual/augmented reality (VR/AR), behavioural measures involve collecting data on users' actions, movements, and interactions within the virtual environment. This data allows us to understand what the person is doing with disruptive technologies and how they behave.

In summary, this project will use both behavioural and psychophysiological measures to analyse and measure learning with disruptive technologies. These measures will provide us with a reliable analysis of the behaviours of the person during the learning process. The use of these measures in each of the cognitive and affective skills and the different tools that will be used for their collection are detailed below.

5. Cognitive and affective skills collected

This proposal aims to establish a new methodological framework, disruptive and non-disruptive, for learning new knowledge in prototypes 1, 2, and 3. To observe the learning process and the use of different cognitive skills, psychophysiological and behavioural metrics will be collected to give us the values of the interaction of the person in the different lessons, on the other hand, the learning acquired will be collected through pre, post scores (a theoretical knowledge test) in each of the lessons.

The measurements will be collected following the CAMIL perspective, which synthesises existing immersive educational research to describe the process of learning in XR. Therefore, following these guidelines, we propose a methodological framework to understand the learning process by using new technologies.

In this project, different technologies (VR, AR, Edison…) are used to teach different flavours of content, such as logical content (prototype 1), social content (prototype 2), and psychomotor content (prototype 3). The differentiation of the contents is due to the different knowledge that is required to be put into practice to learn these new contents, e.g., to be able to understand the tasks to be performed in prototype 2, you have to make enquiries in the social field, about social relations and interactions between people that are exposed in the lessons.

As different modules of the prototypes use different technologies, appropriate measurement parameters will be collected.

5.1 Cognitive load

Cognitive load measurement gives us a value describing the difficulty of the task and the stress it causes for the participant. Research indicates that biometric indicators rise proportionally with mental effort. Therefore, our models integrate data from various sources, including the **heart rate** (PPG, pulse plethysmography), **the pupil (pupillometry), and gaze behaviour (eye tracking)**.

Additionally, to measure this parameter in lessons without virtual reality devices, the values of **psychophysiological measures such as EDA** (Romine, et al,.2022) will be used. To carry out this analysis, a significant increase in the level of these metrics will be detected and the subsequent effectiveness of the task will be checked, observing whether this increase in psychophysiological activation affects performance and, therefore, presents symptoms of cognitive load.

5.2 Interest

Interest is made up of curiosity and attention, so to understand how interested a person is in learning certain subjects, it is necessary to measure attention and curiosity. By measuring these two cognitive skills, we will have a parameter of the interest that a person has when new content is presented. Curiosity and attention are going to be measured through questionnaires before and after the XR starts, while psychophysiological and behavioural measures are going to be collected during the XR experience.

Attention in the VR lesson will be measured by **eye-tracking** (Mendez-Encinas, et al.,2023). Collecting the places and objects that the participant looks inside the XR environment.

For those lessons that do not use the VR headset, **behavioural measures** are going to be collected. These behavioural measures refer to the time and actions that the participant does while learning in the extended environment.

Curiosity is going to be measured by the ET (Hoppe, S., Loetscher, T., Morey, S., & Bulling, A. 2015). This allows us to collect data on the areas of interest that the person looks at the most. For those lessons which use different technology, the behavioural data is collected. For example, in the data analysis, we will be able to see which places the person visited the most if the participant repeated movements, or the time of each action.

5.3 Self-efficacy

Self-efficacy is related to physical and emotional arousal. Consequently, there is a direct correlation between an individual's self-efficacy and the emotions the student has while learning. A high sense of self-efficacy is associated with positive activating feelings such as happiness, enthusiasm, and hope, whereas lower self-efficacy is linked to negative emotions that inhibit activation, such as boredom, anxiety, and anger. Self-efficacy beliefs can influence perceived stress and corresponding physical reactions. Students often view stress and anxiety as weaknesses that will lead to poor performance, while those with positive emotions bolster their self-efficacy and are likely to perform better (Gerostathi, M., Doukakis, S. 2023).

In all the lessons, **behavioural data** will be collected to compare the action flow of each lesson and participant. During each lesson, **psychophysiological measures** are going to be collected to correlate with behavioural measures. Additionally, some questions will be asked during the post-XR environment in each lesson.

5.4 Motivation

The measures of motivation are linked to interest (Tan, A. L., Gillies, R., & Jamaludin, A. 2021). Because of this, they are going to be taken into account together. Motivation level and type are going to be taken from the Locus of control questionnaire which the participant is going to do before the XR lesson starts. This questionnaire will allow us to understand if the participant has an intrinsic or extrinsic motivation. During the XR lessons, **behavioural and psychophysiological measures (HR and EDA)** are going to be collected. The data collected with these two metrics allows us to understand if the motivation stands the same during the learning process. This analysis allows us to see the changes in student performance.

5.5 Emotional self-regulation

Emotional self-regulation is measured by the use of psychophysiological metrics such as EDA and HR. Studies have found that positive emotions enhance cognitive and motivational regulatory processes, which in turn lead to academic success (Dindar et al., 2020). **EDA and HR** data will be collected in all the lessons. The data analysis of these metrics gives us valid information about the emotional state of each lesson and how the person regulates the behaviour during and after each lesson. Understanding which one can be more stressful and therefore contain a higher cognitive load and on which one the arousal state at the same level.

5.6 Embodiment

Embodiment is an important characteristic in the CAMIL theory used in this project, due to the use of different technologies: virtual reality through glasses, augmented reality through glasses, but also through no immersive technologies. This leads to different types of embodiments.Screens lack embodiment primarily due to technological constraints, design considerations, and their intended purpose.

Hence, embodiment will be measured by means of the **presence and agency questionnaires** included in the usability sections of each of the prototypes which use technology that allows to measure embodiment..

7. Conclusions

This deliverable explores learning and the cognitive skills that interact during the acquisition of new knowledge in e-learning. Here, we propose a theoretical approach to understanding learning aided by disruptive technologies and the mechanisms underlying this process. For which a question is posed: are disruptive technologies enhancing learning? In order to answer this question in a concise way, the following questions are structured to answer the general objective of the project. The questions raised are as follows (RQ1), Which technologies are considered most useful in literature? (RQ2) What mechanisms are considered in the literature to model the effect of learning contexts or types of content? and the last is (RQ3) What does the literature say on how cognitive and emotional skills are most useful to enhance the learning mediated by technologies?

First of all, it was found necessary to understand what learning is and what the difference is between traditional learning and learning mediated by disruptive technologies. Emerging disruptive technologies have promoted a move towards an experiential learning model that emphasises the value of hands-on practice and practical application. This disruptive technology uses digital platforms and interactive tools, encouraging active and collaborative student participation. Resources are dynamic and accessible at any time, and assessments include immediate feedback and progress analysis. This approach enables decentralised and global access to information, optimising the educational experience and academic outcomes. Meanwhile, Traditional learning is characterised by face-to-face and direct teaching methods, with students as passive recipients of information and limited interaction. Learning materials are static and assessment is done through written exams.

This project aims to explore the efficacy of learning using disruptive technologies, therefore, there is a need to find a methodology for effective learning, but the characteristics of the student cannot be underestimated, as it is the student who has to acquire the new content shown. The student has some basic cognitive characteristics that allow them to process the learning of new contents, the variability in these characteristics can be determinant for the acquisition of knowledge, as explained by the immersive learning model.

To understand the process a person undergoes in learning with disruptive technologies, the cognitive and affective model of immersive technologies (CAMIL) (Makransky & Petersen, 2021) is proposed which refers to a framework for understanding how virtual reality (VR), augmented reality (AR), and other immersive and disruptive technologies impact both cognitive processes (such as perception, attention, memory, and decision-making) and affective responses (emotions, attitudes, and behaviours) of users.

In learning with disruptive technologies like VR and AR, affective responses play a significant role in influencing users' engagement and learning outcomes. The Cognitive Affective Model of Immersive Learning (CAMIL) acknowledges the importance of traditional learning theories while highlighting the unique affordances of XR, particularly presence and agency. CAMIL identifies six key cognitive and affective factors.

Firstly, interest is defined as the connection between an individual and a specific topic, blending affective and cognitive elements. The second skill is intrinsic motivation, the internal processes that energize, direct, and sustain behaviour toward achieving a goal. The third feature, self-efficacy refers to individuals' confidence in their ability to manage challenging tasks and their overall functioning. Fourthly, embodiment refers to the phenomenon where cognitive processes are deeply influenced by the physical body and its interactions with the environment. Cognitive load refers to the amount of mental effort required to process information or perform tasks, impacting learning and problem-solving effectiveness. The last of the cognitive and affective skills is self-regulation involves the ability of individuals to manage their thoughts, emotions, and behaviours to achieve personal goals and adapt to various situations effectively. All these skills contribute to knowledge acquisition and transfer using disruptive technologies as a tool for learning.

These cognitive skills modulate learning, making it more or less effective depending on how these characteristics interact with the presented content and the technologies used. To measure these cognitive processes, behavioural and psychophysiological measures are chosen, as they are implicit measures that can be collected while the person performs different tasks. These implicit measures gather information about the activation state of the nervous system, which is related to the mood and emotional states the person experiences during the task. The chosen measures are:

- EDA: Electrodermal activity refers to the measurement of changes in skin conductance, which are influenced by the activity of the autonomic nervous system, specifically the response of sweat glands. These changes reflect the level of emotional arousal and can provide information about states of stress, anxiety, and other affective and cognitive processes. EDA is an implicit and non-invasive measure, widely used to investigate emotional and physiological responses during various tasks and stimuli in experimental contexts.
- Heart rate variability (HRV) refers to the fluctuation in the intervals between consecutive heartbeats, reflecting the activity of the autonomic nervous system. HRV is an indicator of the body's ability to adapt to changes and manage stress, with higher variability associated with

better health and emotional resilience. In experimental contexts, HRV is used to assess the body's response to different emotional states, stress levels, and cognitive processes, providing an implicit and non-invasive measure of emotional regulation and autonomic flexibility.

- ET is a technique that measures and records eye movements to analyze how individuals perceive and process visual information. This tool enables the identification of visual elements that capture attention, the duration of fixation on specific points, and the pattern of visual scanning. Eye tracking is used to investigate cognitive, emotional, and behavioural processes, providing precise data on visual attention and preferences in a variety of experimental and applied contexts.
- Behavioural State: In virtual/augmented reality (VR/AR), behavioural measures involve collecting data on users' actions, movements, and interactions within the virtual environment. This data allows us to understand what the person is doing inside the immersive environment and how they behave.

All these measures will be used to analyse learning and the influence of cognitive and affective variables. The following table summarises the use of each of these psychophysiological and behavioural measures to analyse various cognitive and affective characteristics and thus measure their influence on the learning process mediated by disruptive technologies.

Cognitive load	***Interest***		***Motivation***	***Self-efficacy***	***Emotional self-regulation***
	curiosity	***Attention***			
ET,EDA, HR	ET and behavior	ET and behaviour	Behaviour, EDA	Behaviour, EDA AND HR	Behaviour, EDA AND HR

Table 1: summary of the cognitive skills and the measures collected

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