AI4ED

TOWARDS AN AI DRIVEN EDUCATIONAL PROCESS
INTEGRATING MODERN CAREERS IN THE EDUCATIONAL SYSTEM

Deliverable

D2.1 - AI4Ed Implementation of Active Learning Pedagogy in AI Driven Processes

Deliverable Lead: University of Zaragoza
Deliverable due date: 31/05/23
Actual submission date: 03/08/23
Dissemination level: PU
Version: COMPLETE

Co-funded by the European Union

This project has received funding from the European Union's Erasmus + programme under grant agreement No 101087543
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Document Control Page	
Title	AI4Ed Implementation of Active Learning Pedagogy in AI Driven Processes
Creator	Universidad de Zaragoza
Description	Definition of KPIs that AI4Ed will use
Contributors	All partners
Creation date	19/06/2023
Type	Report
Language	English
Audience	☒ public ☐ confidential
Review status	☐ Draft ☐ Assigned Reviewer accepted ☒ Coordinator accepted
Action requested	☐ to be revised by the Assigned Reviewer ☐ for approval by the Project Coordinator ☐ for acknowledgement by Partners

Revision history

Version	Author(s)	Changes	Date
V0	UNIZAR	Document creation	03/07/2023
V0.1	UBREMEN	Revision	22/07/2023
V0.2	IMH	Revision	20/07/2023
V0.3	SCSKZ	Revision	17/07/2023
V0.4	CENFIM	Revision	22/07/2023
V1	UNIZAR	Addition of partners comments	25/07/2023
V1.1	UNIZAR	Addition of partners comments	26/07/2023
V1.2	UNIZAR	Addition of partners comments	28/07/2023
V1.3	UNIZAR	Addition of partners comments	31/07/2023
V2	UNIZAR	Final Revision and editing	03/08/2023

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Glossary

AI	Artificial Intelligence
BPN	Basic Psychological Needs Theory
CTML	Cognitive Theory of Multimedia Learning
IAA	Interactive Audiovisual Activity
KPI	Key Performing Indicator
MDA	Mechanics-Dynamics-Aesthetics
SDT	Self-Determination Theory
VET	Vocational Education and Training

EXECUTIVE SUMMARY / ABSTRACT

Abstract	This report is part of the deliverables of Work Package 2 (Definition of the AI strategy in educational processes), D2.1 AI4Ed Implementation of Active Learning Pedagogy in AI Driven Processes. The report will be based on the approach to use some theories or models related to the different learning styles, from which we supervised learning based on training to find the best learning results and unsupervised, to find through clustering data patterns to group those that have common aspects. The report is divided into four main parts: a theoretical framework including theoretical models, identification and selection of KPI and conclusions.
Keywords	AI, KPI, Active learning pedagogy

1 Introduction

The project AI4Ed will address a long-term strategic vision to provide through AI a personalised tutoring according to the student´s/apprentice`s needs and learning capabilities and promoting collaborative learning by developing a problem-based teaching-learning model. This will be achieved by developing a theoretical framework in which to identify pedagogy based KPIs and integrating them in AI systems.

This document intends to give a general vision of the different learning needs and how they could be supervised under the umbrella of the AI learning processes. It is also a summary of the selected KPIs defined for the AI system that will lead to a personalised tutoring, active learning and dropout prevention. For this, it is necessary to know and analyse the theoretical teaching models, associate them with the necessary competences in the students to achieve success and avoid dropping out (Rieckmann, 2012), and make these competences operational in items for the AI. Exceeding the learning needs of higher education students/apprentices with the virtues of AI holds tremendous importance in transforming the educational landscape. AI-powered solutions have the unique capability to personalize and enhance the learning experience for each student, catering to their individual strengths, weaknesses, and preferences. By leveraging AI algorithms, high educational institutions can analyse vast amounts of data on students' performance, engagement levels, and learning styles, enabling them to provide tailored content and resources to address specific learning gaps (Haleem, Javaid, Qadri, & Suman, 2022).

A review study analysed that the use of AI in higher education has been increasing in recent years, although the European Union is not the region where it is being implemented the most. This study concludes that there are five main uses of AI in higher education:

(1) Assessment/Evaluation,

(2) Prediction,

(3) AI Assistant,

(4) Intelligent Tutoring Systems, and

(5) Managing Student Learning (Crompton & Burke, 2023).

To explore how AI can effectively assist students in acquiring skills and competencies to become active citizens, several critical questions arise. These questions centre around what students should be learning and how AI can be employed to design, represent, and assess such learning experiences.

The answers to these questions are fundamental to the ongoing debate about what constitutes effective learning and how AI can cater to the individual needs of students. A high-level perspective of “good learning” involves it being an active, cumulative, individual, self-regulated, goal-oriented, situated, and, above all, a student-centred experience that facilitates knowledge construction.

Designing AI systems with a focus on the student at the core of the learning process, rather than solely on the technology, could be a significant advancement. This approach encourages a departure from deterministic technology usage and moves toward a more comprehensive approach that involves classifying meaningful and pedagogically coherent attributes. In an ideal scenario of technology-enhanced learning, AI would have the capacity to adapt to the unique needs and interests of each student, supporting them in gaining confidence and skill in managing their own learning journey (Lameras & Arnab, 2022).

AI-driven analytics can help educational institutions identify areas for improvement in their teaching methods, and finding the stands for key performance indicators. By harnessing AI's potential, higher education institutions can create a more dynamic and adaptive learning environment that meets the ever-evolving needs of their diverse student/apprentice population. This may create more sustainable and expandable educational scenarios in the future (Tejedor et al., 2019). Educational institutions leveraging AI extensively incorporate e-learning environments to enhance teaching and learning experiences, accompanied by a variety of educational activities. E-learning, or online learning, plays a vital role higher education. However, there is a challenge in effectively implementing e-learning higher education system to enhance course resources, predict student learning styles, improve teaching quality, and provide robust service support (Fu, Krishna, & Sabitha 2022).

The implementation of active learning pedagogy in AI-driven processes holds immense significance in the realm of education and problem-solving. Active learning, a psychocognitive approach that encourages students/apprentices to engage actively in the learning process through hands-on activities, discussions, and problem-solving, can be effectively integrated into AI-driven systems to enhance their performance and adaptability. These active learning techniques have to correspond to adequate didactic models (Rieckmann, 2012). The AI allows these teaching models to be optimized, and conversely, the teaching models indicate to the AI which items are educationally relevant. Through this integration, AI can analyse vast amounts of data on student engagement, performance, and interactions to identify personalized learning pathways and provide tailored content that fosters academic growth (Haleem, et al, 2022). Furthermore, AI-driven analytics can detect early signs of struggle or disengagement, enabling timely interventions to support struggling students and prevent dropout, which is one of the purposes of this project. By incorporating active learning techniques, AI models can continuously learn from new data, making them more proficient at recognizing patterns, improving decision-making, and optimizing their overall functionality.

2 Theoretical foundation

In this section we will base and explain the Cognitive Theory of Multimedia Learning (CTML) that supports effective learning and the pedagogical approach that supports effective teaching in current technological contexts. Subsequently, some of the didactic methods and their relationship with the potential of AI in education will be exposed.

In the last hundred years there have been great advances both in the science of learning and in the science of teaching. There are three major theoretical models that attempt to explain and guide both phenomena: behaviourism, cognitivism and constructivism.

Behaviourism is nourished by the great contributions of Skinner (1953), especially linked to effective evaluation based on educational feedback, and as today can be seen in any computer application with loyalty strategies, or to avoid abandonment, or even in research on AI based on machine learning by reinforcement.

Cognitivism, along with Piaget (2001), made it possible to focus attention on learners' internal processes, their thinking, and the mental processing of information. Specifically, it later allowed the neo-Piagetian theories to be opened, which developed key phenomena for learning such as working memory or mental images —and allowing the specific approach of computationism and connectionism applied to AI—.

Finally, **constructivism** contributed a crucial point (Ausubel, 1968): the necessity of active student/apprentice participation, whether it is understood as a behavioural, mental, or practical engagement. Directed attention, intention, and motivation towards learning become very relevant. This theory, inspired by pragmatism pedagogy (Dewey, 1897), establishes a direct link between how students learn and how they can and should be taught. Now, we can discuss the role of a teaching agent, which may be a teacher, fellow classmates, or a virtual environment for automated and AI-based learning. Ausubel introduced key concepts such as meaningful learning and emphasized ***the most important aspect of producing learning: understanding each student's/apprentice's real starting point to create rich and challenging situations accordingly.*** Today, this can be optimized with dynamic AI systems that leverage relevant data from each student/apprentice.

The three macro theories explained —behaviourism, cognitivism and constructivism— have given rise to new current models that integrate many of its virtues. These macro theories are the antecedents of the most current theories that will be used in the present project. The advantage of starting from existing and integrating theories is that they will enable the discovery of relevant foundations for Key Performance Indicators (KPIs) to create a predictive and valuable AI, irrespective of the macro-theories of origin.

A theoretical model helps in operationalizing a theory. One of those models, with scientific and educational support, is the Cognitive Theory of Multimedia Learning (CTML) —originally called "model of meaningful learning"—. Knowing the three previous macrotheories allows us to understand the background of CTML. The CTML, proposed by Mayer (2014), is a theoretical framework that explains how students/apprentices learn from multimedia presentations, which involve both words and visuals. According to Mayer (2014, pp. 46-52), learning is an active process of mental construction, and effective multimedia design should facilitate this process. The theory emphasizes two main cognitive channels for processing information: the auditory/verbal channel for processing spoken or written words, and the visual/pictorial channel for processing images or animations. Mayer highlights three key principles:

1) Dual channels: humans possess separate channels for processing visual and auditory information, thus multimedia should leverage both channels by presenting complementary, rather than redundant, information;

2) Limited capacity: Humans are limited in the amount of information that can be processed in each channel at one time, thus the design should respect the cognitive limitations of learners' working memory by avoiding cognitive overload;

3) active processing: humans engage in active learning by attending to relevant incoming information, organizing selected information into coherent mental representations, and integrating mental representations with other knowledge, thus, learners should be actively engaged in the learning process through appropriate pacing and content organization.

By aligning AI driven educational process and multimedia materials with these principles, it can be optimized the effectiveness of instructional presentations, enhance learning outcomes and abandon dropout in higher education.

The core assumption driving research on multimedia learning is that instructional messages tailored to align with the functioning of the human mind are more likely to foster meaningful learning compared to those not designed accordingly. This hypothesis forms the basis of the CTML, which relies on three key cognitive science principles of learning (Figure 1): dual channels, limited capacity, and active processing.

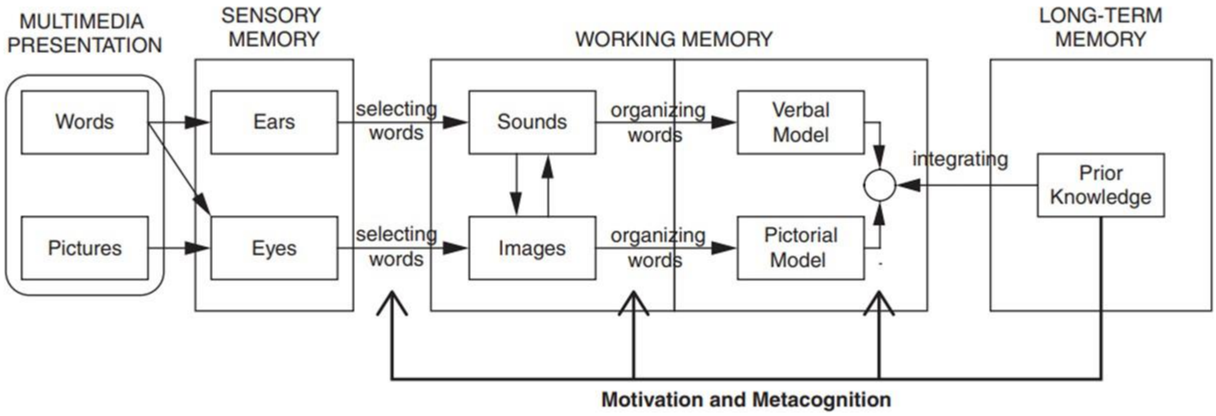

Figure 1 - Outline of the3 Cognitive Theory of Multimedia Learning (extracted from Mayer, 2014, p. 66)

Firstly, the dual-channels assumption (Paidivio, 2006). This assumption in the CTML posits that humans possess distinct information processing channels for visually/spatially represented material and auditorily/verbally represented material. This means that when information is presented visually (e.g., illustrations, animations, on-screen text), it is initially processed in the visual channel, while information presented auditorily (e.g., narration, nonverbal sounds) is processed first in the auditory channel.

This concept of separate information processing channels has a well-established history in cognitive psychology and is closely associated with Paidivio's dual-coding theory and Baddeley's model of working memory. In essence, the relevance of the dual-channel assumption lies in its proposition that the human information processing system accommodates both auditory/verbal and visual/pictorial channels for handling information, which has significant implications for understanding how individuals learn from multimedia presentations. The human information processing system is believed to have dual channels for visual/pictorial and auditory/verbal processing, each with limited capacity (Mayer, 2009).

What undergoes processing in each channel? There are two perspectives to distinguish the dissimilarities between the two channels: one revolves around representation modes, and the other centres on sensory modalities. The representation-mode approach examines whether the stimulus presented is verbal (e.g., spoken or printed words) or nonverbal (e.g., pictures, video, animation, or background sounds). Following this approach, one channel handles verbal material, while the other processes pictorial material and nonverbal sounds. Conversely, the sensory-modality approach centres on whether learners first process the presented materials visually (e.g., pictures, video, animation, or printed words) or auditorily (e.g., spoken words or background sounds). Following this perspective, one channel deals with visually represented material, while the other handles auditorily represented material (Mayer, 2009).

There are interactions between the channels. Although information enters the student/apprentice information system through one channel, learners have the ability to transform the representation for processing in the other channel. When learners can allocate sufficient cognitive resources to the task, information initially presented in one channel can also be represented in the other. For instance, consider a video of a musical performance, which is primarily processed in the visual channel due to its presentation to the eyes. However, a skilled musician may mentally convert the visual performance into musical notes and tones, engaging the auditory channel as well. Similarly, a person viewing a complex infographic about a historical event may initially process the visual information, but with enough focus, they could mentally articulate a comprehensive verbal explanation of the same event, utilizing the auditory channel. Conversely, a piece of poetry, initially processed in the auditory channel as it is recited, may evoke vivid mental images and visual scenes when the listener actively engages in forming mental pictures. Similarly, when presented with a series of pictures illustrating the different stages of a scientific experiment, a scientist might mentally translate those visuals into a step-by-step verbal description, enriching the auditory channel with supplementary details. The practical consequences of this at the didactic design level is that the information must be presented in both verbal and visual formats, among others. AI can both collect textual and pictorial information and create it.

Secondly, the limited capacity assumption, based on Baddeley's model of working memory (Baddeley, 1999). Working memory is one of the executive functions currently highly studied, and which are predictors of learning and learning intention in high education contexts (Jozsa, Oo, Amukune, & Jozsa, 2022). Working memory functions as an executive aspect of cognition. When exploring cognitive development in the higher education population, it is crucial to view it as a multidimensional and multidirectional concept. The executive functions encompass both cognitive and emotional processes that play a vital role in coordinating information processing and action control. These functions involve organizing tasks, setting objectives, initiating and executing plans, inhibiting distractions, detecting errors, devising strategies, and ensuring goal achievement. It's essential to acknowledge that these processes occur within the brain and are subject to modification due to cerebral plasticity, which defines their adaptability and potential for change. Brain development and executive functioning exhibit variations throughout different stages of life. The period from birth to around 12 years of age is marked by exponential development. As individuals approach approximately 20 years of age, a level of stability is attained. However, from the age of 60, a decline in executive functioning starts to manifest. It is important to note that the need to exercise and nurture these functions is not limited to the early growth period alone. Instead, they should be regarded as an essential subject of study and work throughout adulthood as well. Maintaining and enhancing executive functions can significantly contribute to cognitive well-being and overall cognitive abilities as individuals age (Shanmugan & Satterthwaite, 2016). When designing an efficient educational AI, it is crucial to consider the constraints of working memory, which serves as a limited executive function. Students/apprentices heavily rely on it to retain essential concepts, instructions, numbers, and other information. Moreover, flexibility holds significant importance, especially in situations where adaptation to environmental demands becomes necessary. This adaptive quality also plays a fundamental role in problem-solving, fostering creativity and the ability to approach challenges with flexibility and innovation. By acknowledging and incorporating these aspects into the development of educational AI, it can be created a more effective and supportive learning environment for students//apprentices (Karyotaki & Drigas, 2015).

This second assumption suggests that humans have limitations in processing information within each channel simultaneously. When presented with an illustration or animation, the learner can only retain a few images in their visual working memory at any given moment, representing parts of the presented material rather than an exact replica (Mayer, 2011). For instance, if shown an illustration or animation of a bustling city scene, the learner might concentrate on forming mental images of the traffic flow, pedestrians crossing the street, and colourful billboards. Similarly, when listening to a narration, the learner's verbal channel in working memory can only grasp a few words at once, reflecting segments of the presented text rather than a word-for-word account. For example, if the spoken text is "Amelia was wandering through the enchanted forest, surrounded by tall trees, singing birds, and magical creatures," the learner may retain the following verbal fragments in their auditory working memory: "Amelia wandering," "enchanted forest," and "magical creatures". In both cases, the learner's ability to retain information is limited, and they focus on essential elements, allowing them to process and comprehend the content effectively. This phenomenon is associated with the "magical number seven" (Miller, 1956). This phenomenon is associated with the "magical number seven", which explains that a student/apprentice directly detects the exact number of elements when they are seven or less, but when there are more, they make an estimate. Although there are individual differences, on average, memory span is fairly small – approximately five to seven chunks (Mayer, 2014). The direct consequence of this in teaching is to limit the number of elements that are presented at the same time so as not to saturate the learner's working memory, and thus optimize learning moments.

So, the limited cognitive resources are distributed in different ways. The limitations on the processing capacity compel us to decide which incoming information deserves our attention, the extent to which we should establish connections among the chosen pieces of information, and the degree to which we should link selected pieces of information with our existing knowledge. *Metacognitive* strategies (Figure 2) refer to methods used to allocate, monitor, coordinate, and adapt these restricted cognitive resources effectively. The aim is to optimize the utilization of our cognitive abilities and enhance learning and understanding. An effective strategy to manage limited cognitive capacity is to generate tasks, questions, or situations through AI that encourage metacognition in the student/apprentice (Snow, Jacovina, & McNamara 2015). Metacognition is related with self-regulated learning processes. Self-regulated students//apprentices take an active role in their learning journey and have the autonomy to choose from a range of strategic approaches while closely monitoring their progress towards the desired outcome. The suggested AI-driven solution has been utilized to track student/apprentice behaviour by analysing their feedback and responses (Huang, Dong, & Vignesh, 2022; Lameras et al, 2022).

Thirdly, the active processing assumption, already addressed by the pragmatist pedagogical tradition (Dewey, 1897), and further developed by subsequent pedagogical constructivism (Ausubel, 1960, 1968). According to the CTML theory that we maintain in this project (Mayer, 2014), active processing involves humans actively engaging in cognitive activities to construct a meaningful mental representation of their experiences. These cognitive processes encompass paying focused attention to relevant incoming information, organizing it into a coherent cognitive structure, and integrating it with existing knowledge. In essence, humans act as dynamic processors, striving to comprehend multimedia presentations. This perspective of humans as active processors contradicts the conventional view of them as passive recipients who merely store vast amounts of information in memory, akin to tape recorders, for later retrieval.

Active learning takes place when a learner engages in cognitive processes to actively process incoming material, with the intention of comprehending the content. The ultimate goal of this active cognitive processing is to create a coherent mental representation, making active learning akin to a process of model building. Within this mental model or knowledge structure, essential components of the presented material and their relationships are represented. For instance, in a multimedia presentation explaining how lightning storms form, the learner might attempt to construct a cause-and-effect system, where changes in one part of the system lead to changes in another part.

Similarly, when comparing and contrasting two theories in a lesson, the process of constructing a mental model involves building a matrix-like structure that evaluates and contrasts the two theories across various dimensions (Mayer, 2011; Mayer, 2014).

Active learning takes place when a learner actively engages cognitive processes to comprehend incoming information effectively. This process aims to construct a coherent mental representation, making active learning akin to a process of model building. The mental model, or knowledge structure, represents the fundamental components of the presented material and their interconnections. For instance, when exposed to a complex historical event, the learner might attempt to create a chronological sequence of cause-and-effect events that led to significant outcomes. In another scenario, during a scientific experiment, the learner could construct a mental model that identifies variables and their relationships within an experimental setup. Similarly, when analysing a literary work, the construction of a mental model might involve building a thematic framework that highlights recurring motifs and character developments throughout the text. An AI system designed with active learning principles can facilitate deeper comprehension by encouraging learners to actively engage in cognitive processes, construct coherent mental representations, and develop knowledge structures. Such an AI can personalize learning experiences by tailoring content and activities based on individual learners' cognitive strengths and preferences. By assisting students/apprentices in building mental models across various subjects like history, science, and literature, the AI can provide real-time feedback, identify learning gaps, and support lifelong learning journeys, ultimately enhancing the effectiveness and efficiency of education through technology (Fu, et al., 2022; Huang et al., 2022).

When active learning leads to the development of a coherent mental representation, it becomes valuable to explore the typical methods of knowledge structuring. Process structures can be illustrated through cause-and-effect chains, providing explanations of how certain systems function, like explaining the workings of the human ear (Mayer, 2014). On the other hand, comparison structures can be presented as matrices, allowing comparisons between two or more elements along multiple dimensions. Three essential cognitive processes play a crucial role in active learning (Figure 2): selecting relevant material, organizing the chosen material, and integrating it with existing knowledge. Selecting relevant material involves the learner's focus on pertinent words and images from the presented material, bringing this information into the working memory. Mayer (2014, p. 51) defines it as follows: "*Attending to relevant material in the presented lesson for transfer to working memory*". Organizing selected material involves establishing structural relationships among the elements, possibly utilizing one of the five structures described earlier: "*Mentally organizing selected information into a coherent cognitive structure in working memory*" (p. 51). This process occurs within the working memory. Integrating selected material with existing knowledge entails creating connections between incoming information and relevant prior knowledge: "*Connecting cognitive structures with each other and with relevant prior knowledge activated from long-term memory*" (p. 51). In this process, knowledge in long-term memory is activated and brought into the working memory. For instance, when presented with a multimedia message about the causes of lightning, learners must attend to specific words and images, arrange them into a cause-and-effect chain, and relate these steps to prior knowledge, such as the principle that hot air rises.

Finally, the CTML theory defines three types of memory that are relevant for designing teaching and learning situations, as depicted in Figure 2.

Memory store	Description	Capacity	Duration	Format
Sensory memory	Briefly holds sensory copies of incoming words and pictures	Unlimited	Very brief	Visual or auditory sensory images
Working memory	Allows for manipulating selected incoming information	Limited	Short	Verbal and pictorial representations
Long-term memory	Permanently stores organized knowledge	Unlimited	Permanent	Knowledge

Figure 2 - Three memory stores in the CTML (Extracted form Mayer, 2014, p.53)

To summarize, the CTML proposes that people learn from words and pictures by utilizing separate channels for processing verbal and visual material (dual-channel assumption). Each of these channels has a limited capacity, enabling the processing of only a small amount of material at a time (limited-capacity assumption). The theory further suggests that meaningful learning occurs when learners actively engage in appropriate cognitive processing during the learning process (active processing assumption). This theory guides and makes it possible to operationalize the relevant variables to create an AI-led system for learning.

However, one of the current shortcomings of the theory is the lack of a deep development of the motivation towards learning, which Mayer himself affirms (2014, pp. 65-67). Therefore, to enhance the richness of this project, it has been decided to complement the CTML theory with the Self-Determination Theory (SDT) and integrate it with the theory of gamification using AI.

The Self-Determination Theory (SDT) is a comprehensive theory in human psychology that focuses on motivation, development, and well-being. Likewise, this theory is nourished by the bases of behaviorism, cognitivism and constructivism. This theory has been proposed and developed by Deci and Ryan for 30 years. It centers around the concept of autonomy, which involves the ability to regulate one's own behavior within a social context of influence (Ryan & Deci, 2017, p. 79). This theory has found extensive application in the field of education (Ryan & Deci, 2017, pp. 351-357) and has proven successful in gaming and gamification contexts as well (Sailer, Hense, Mayr, & Mandl, 2017).

The Cognitive Evaluation Theory, a sub theory of the aforementioned one, focuses on the influence of social contexts, including external events like rewards, on motivation (Sailer et al., 2017).

In contrast, the Organismic Integration Theory, the second sub-theory, proposes that motivation exists on a continuum with varying degrees of self-determination. This continuum encompasses intrinsic motivation, extrinsic motivation, and demotivation. Intrinsic motivation involves engaging in an activity for the pleasure and satisfaction derived from the activity itself. On the other hand, extrinsic motivation entails participating in and committing to an activity as a means to achieve something, rather than for the intrinsic enjoyment of the activity.

SDT has already been studied in a compatible way with the orientation of AI in education. A study (Chiu & Chai, 2020) suggests that genuine curricular creation should incorporate four forms of curricular design approaches, all guided by teachers' self-determination in orchestrating students'/apprentice's learning experiences. These four forms include:

- content,
- Product,
- process, and
- praxis.

Another study demonstrated the suitability of the self-determination approach to integrate AI into education, albeit in this instance as learning content rather than as a design tool (Xia et al., 2022).

The Basic Psychological Needs Theory (BPN), another subtheory of SDT, establishes three inherent needs that promote optimal motivation and well-being (Deci et al., 2000). Firstly, the need for competence involves the belief in one's ability to perform a task efficiently and effectively. Secondly, the need for autonomy, or self-determination, stems from the desire to experience an internal sense of causation, where one feels in control of their actions. Finally, the need for social relationships pertains to a sense of belongingness and connection with others (Ryan & Deci, 2017, pp. 96-97).

Gamification is one approach to design educational environments in a manner that allows for the operationalization of the principles of SDT. Gamification involves incorporating elements of videogame (Quintas, 2022, p. 198), design into non-recreational contexts (Deterding, Dixon, Khaled & Nacke, 2011) with the purpose of influencing people's behavior and motivation (Kapp, 2012). In the realm of education, we refer to this as educational gamification, where the aim is to modify student/apprentice behaviors towards learning by leveraging actions that influence their motivation. Gamification is particularly suitable due to its widespread presence in numerous applications and educational software. Its implementation encourages continued usage and prevents abandonment or disengagement. A scientifically and pedagogically grounded gamification approach can be customized to suit any program or initiative, creating enriching learning environments.

For instance, Moodle can be gamified, even though it wasn't originally designed for it. The process of gamification involves implementing specific elements rather than directly using video games, making it feasible to integrate educational measures through AI and align them with the desired objectives.

A theoretical model helps in operationalizing a macro-theory. To operationalize the SDT and the CTML in the KPIs that will be explained later, the Mechanics-Dynamics-Aesthetics (MDA) model will be used, whose approach to the educational field has already been developed (Quintas, 2022). This model, although it was born imitating video game engineers, has spread as a design applicable to other contexts, such as education.

This allows transferring the advantages that have been seen in other areas in the more specifically training area. The MDA model refers to the following three pillars:

1) **Mechanics:** it is the set of constitutive elements of the system, the relationship between them, and the way in which it can function routinely a system. It determines the limits of how you can play or act within the system. This is the aspect of the model that the designer-teacher can control directly, since the following ones will not be fully controlled. Example in game: in chess the mechanics is the set of pieces that there are, the board, the types of movements that each piece has, the rules of the game, etc. Example in education: when a student-player submits an educational task within the established deadline, he receives 1000 points. The specific bridge elements are: points, badges, results board, rankings, challenges, levels, avatars, customization and virtual-symbolic market (Quintas, 2022, p. 71).

2) **Dynamics:** This aspect refers to the actual functioning of the mechanics, encompassing how the player-student/apprentice interacts with the mechanics. Similar to physics, dynamics in this context relates to the forces that drive movement, which are the player's actions within the framework of the mechanics. These actions are influenced by the player's desires, which, in turn, are shaped by the game mechanics. For example, in a game of chess, the success of the game is determined by one player's dominance over the other, resulting in only one winner. As a result, each player must always act competitively rather than cooperatively if they wish to succeed. The specific moves a player makes with a bishop or a

pawn at a given moment and in a particular direction represent the dynamics of the system. In an educational scenario, the student/ who earns the most points for correctly reading music scores during the week may be awarded the symbolic badge of "Best Music Reader." Various elements applicable to fostering dynamics include reinforcement, stackability, collectability, progress, status, competition, cooperation, and self-expression (Quintas, 2022, p. 72).

3) **Aesthetics:** This aspect encompasses both the sensations and perceptions evoked by the mechanics as it is designed, as well as the sensations and emotions experienced by the player-student while engaging with the system. For example, in chess, the use of mainly two colours, black and white (though subject to change), and the varying shapes of the figures contribute to the overall aesthetics. Similarly, in an educational setting, dividing the class into four groups, each with a unique name and identifying icon, enhances the aesthetics when they collaboratively solve a "trivial" together. In developing the aesthetics of a gamified system, specific elements that could be considered are fun, immersion, satisfaction, pleasure, identity, social belonging, external beauty, and interest. These elements work together to create an engaging and enjoyable experience for the player-student, fostering a sense of attachment to the gamified environment (Quintas, 2022, p. 72).

Figure 3 - MDA model to design didactics and promote motivation towards learning (Quintas, 2022)

Videogames have been designed based on the MDA model (Figure 3). Consequently, it should not be a mystery for teachers and designers to understand that psychology underlies the creation of video games. Each element within the video game structure, such as points, emblems, groups, aesthetics, challenges, and results tables, is meticulously crafted to enhance the psychological pleasure experienced by the gamer. In comparison to non-digital or traditional games, digital games offer a significant advantage: they exponentially amplify all the attributes of a well-regulated game, thus magnifying the player's pleasure. As a result, video games are significantly more interactive, informative, aesthetically appealing, and effective behavior reinforcers than their non-digital counterparts (Quintas, 2019, p. 126).

At an educational level, Paul Gee (2003, pp. 207-212) in his work *What video games have to teach us about learning and literacy* explains 36 principles that explain what and how videogames allow learning. We can extrapolate these principles from video games to Interactive Audiovisual Activity (IAA) in general, so we will refer to the latter to explain these principles. Only the principles that will later be related to the KPIs will be exposed below.

1. Principle of active and critical learning: all aspects of the learning environment encourage active and critical learning, not passive. They would be associated with most of the methodical approaches of the blended teaching scenario.
2. Principle of design: learn and value virtual design, as well as the principles of audiovisual design. Audiovisual aesthetics is fundamental for the infant stage, as is textual.
3. Semiotic principle: learning and coming to appreciate the interrelationships between, and through, multiple sign systems (images, words, actions, symbols, artifacts, etc.). Aspect associated with digital competence in particular.
4. Principle of commitment to learning: learners participate fully committing themselves (putting a lot of effort and dedication) because they feel immersed and identify with the actions that take place within the IAA.
5. Principle of identity: the students/apprentices feel that their real identity has been extended into a virtual identity that compromises them.
6. Self-learning principle: the virtual world has been built in such a way that learners can learn not only about the IAA domain, but also about themselves and their current and potential abilities. The IAA promotes student autonomy.
7. Input amplification principle: for a small input —information input—, learners provide many outputs —products or output information—.
8. Principle of achievement: there are rewards from the beginning of the IAA, differentiated according to the level of learning and the effort required, as well as continuous recognition of achievements.
9. Principle of practice: trainees have many opportunities to practice, but in a context where practicing is not boring, so they spend a lot of time testing.
10. Exploration principle: the audiovisual allows learning through a cycle of exploration-discovery of the virtual world.
11. Principle of multiple paths: the interactive audiovisual activity allows several paths to advance, progress and learn.
12. Principle of situated meaning: the meanings of signs (words, actions, objects, artifacts, symbols, texts, etc.) are always situated from and in personal experience. There are no general or de-contextualized meanings.
13. Principle of the text: the texts are not understood only verbally but are understood in terms of personal experiences.
14. Principle of increment: learning situations are ordered, initially, so that the first cases can lead to generalizations that are useful for the understanding of subsequent cases.
15. Transfer principle: learners can transfer what they learned at the beginning to new problems
16. Principle of cultural models on learning: learning is established taking into account the existence of different methods and ways of learning.
17. Affinity Group Principle: Apprentices constitute an affinity group that is primarily united by efforts, goals, and practices and that does not share ethnicity, gender, age, nationality, or culture (Quintas, 2019, pp. 126-130).

Much of the theoretical work presented in this epigraph is based on the premise that the way how people learn should be compatible with the design of IA multimedia instructional messages. In short, the design of multimedia instructional messages should be sensitive to what we know about how people process information (Mayer, 2009). The CTML represents an attempt to accomplish this goal by describing how people learn from words and pictures, in a way that is consistent with empirical research evidence and being able to be operationalized and optimized with learning analytics and AI (Li, Duffy & Zhang, 2022).

To achieve this goal of uniting theory with practice, the choice of the KPIs that will be explained in the following section have been based in the following general criteria:

- theoretical plausibility –the theory is consistent with principles of learning and principles of teaching design;
- testability –the theory yields predictions that can be developed by AI and tested in scientific research–;
- empirical plausibility –the theory is consistent with empirical research evidence on multimedia learning;
- applicability –the theory is relevant to implementation of active learning pedagogy in AI driven processes.

In summary, in this section the theoretical models of this project have been developed. First, the Cognitive Theory of Multimedia Learning (Mayer, 2014) explains how to optimize teaching and learning at the cognitive level. It has been complemented with the Theory of Self-determination, and especially with the Theory of Basic Psychological Needs (Ryan & Deci, 2017), which provides the motivational-affective vision towards learning. It has been proposed to operationalize these two macro theories with educational gamification, and specifically with mechanical-dynamic-aesthetic model to design technological environments or programs (Quintas, 2019), and with the principles of transferable learning (Gee 2003). With all this theoretical, scientific and pedagogical foundation, the stands for Key Performance Indicator will be developed. A summary of the theoretical approach is shown inFigure 4.

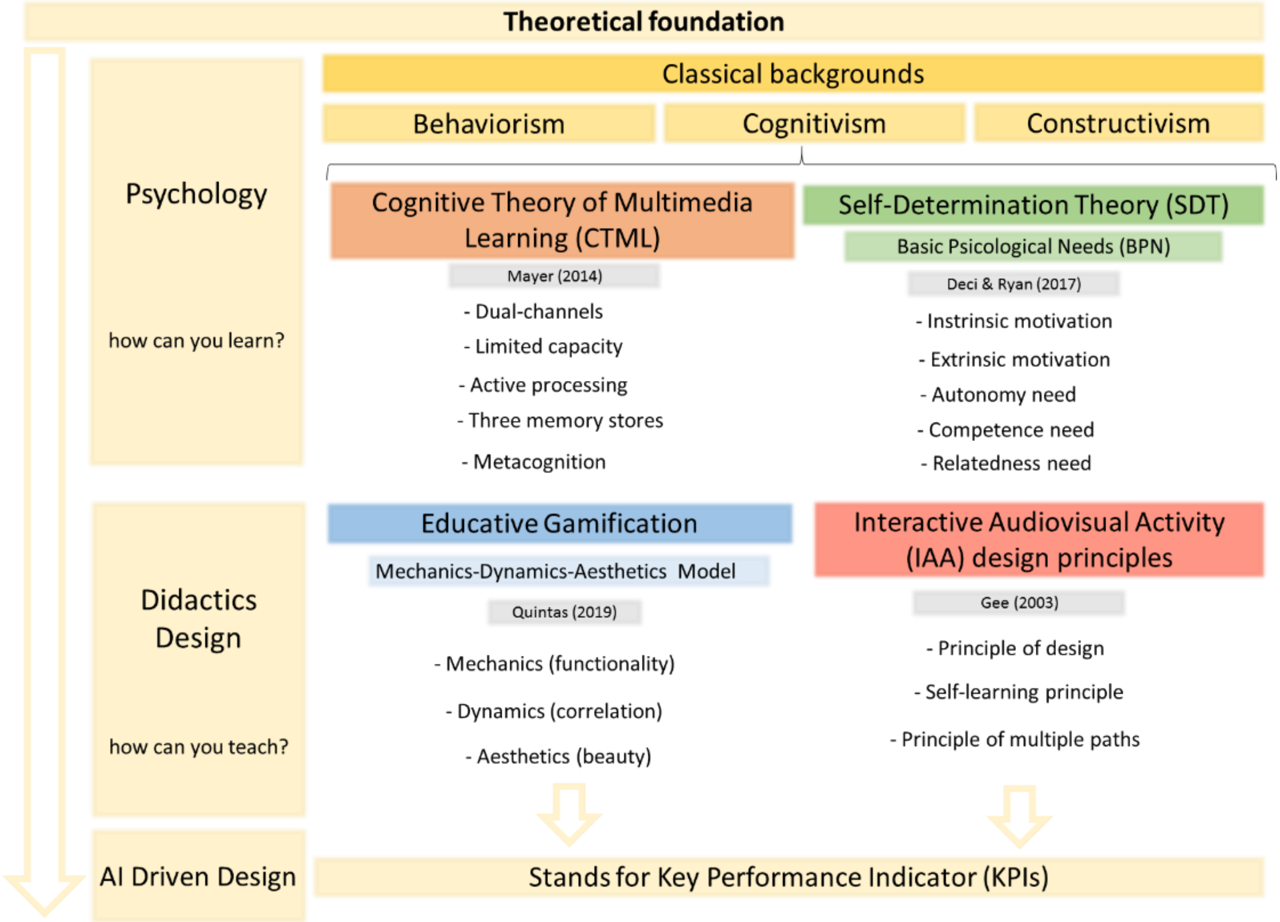

Figure 4 - Summary of the theoretical foundation of AI4Ed

After this revision, it can be concluded that as the field of education continues to evolve, it is imperative to explore diverse learning models that cater to the unique needs of learners. The integration of AI offers promising avenues for enhancing education by providing personalized learning experiences, automating administrative tasks, and creating interactive and immersive learning environments. By embracing AI, educators can unlock new opportunities to engage students/apprentices, foster critical thinking, and prepare them for the challenges of the future.

3 Identification of KPI

KPI (stands for Key Performance Indicator) are measurable values that help organizations to assess their progress towards specific goals or objectives. They are used to evaluate performance, track trends, and make informed decisions. KPIs vary depending on the nature of the organization and its goals, but they should be relevant, specific, measurable, achievable, and time-bound. In this context, it refers to what aspects are related to factors that influence learning through an online platform and specifically with self-learning.

After many meetings and discussions, all the partners converged in an optional set of KPI (to be applied by anyone depending on the laws in force or other requirements) with several features:

- Realistic,
- Possible to obtain,
- According with transparency and ethical principles

A set of KPI were identified following those directions and were grouped by types in Table 1:

Table 1 - Type segmented KPI

KPI	Data Fields	Theoretical foundation
Related to information prior to enrolling in a course – Diagnostic Evaluation	Previous courses	Diagnostic evaluation and personalization (Ausubel, 1968).
	Number of years since last official course	Diagnostic evaluation and personalization (Ausubel, 1968).
	Student's/apprentice`s interests	Diagnostic evaluation and personalization (Ausubel, 1968), instrinsic motivation (Ryan & Deci, 2017), Principle of situated meaning (Gee, 2003)
Related to competences both transversal and directly related to the studies – Individual Competences	Knowledge of the subject	Initial and meaningful knowledge (Ausubel, 1968)
	Use of digital media	Input amplification principle (Gee, 2003)
	Achieve learning objectives	Achievement Principle (Gee, 2003)
	Watching videos (Content consumption)	Dual-channel principle (Mayer, 2014)
	Participation in forums	Relatedness need (Ryan & Deci, 2017)
	Timeline of work	Limited capacity (Mayer, 2014)
	Participation in videoconferences	Principle of commitment to learning (Gee, 2003), active processing (Mayer, 2014)
	Gap in student/apprentice competencies from initial to target level	Meaningful learning (Ausubel, 1958), Incremental principle (Gee, 2003)

KPI	Data Fields	Theoretical foundation
Related to Measuring Academic/VET progress and processes tracking – Individual progress	Average mark (in real time)	Reinforcement principle (Skinner, 1953), Scoreboard, progress (Quintas, 2019).
	Percentage of the competences acquired in real time compared to the target competences	Meaningful learning (Ausubel, 1958), Competence Need (Ryan & Deci, 2017).
	Attendance to the sessions	Reinforcement principle (Skinner, 1953), Principle of commitment to learning (Gee, 2003)
	Percentage of completed assignments	Points, scoreboard, customing, progress (Quintas, 2019).
	Date of submission of the various assignments	Limited capacity (Mayer, 2014), Extrinsic motivation (Ryan & Deci, 2017).
Related to the relevance of the subject – Topic relevance	Feedback and evaluations	Reinforcement principle (Skinner, 1953)
	Popularity of the content/subject	Relatedness Need (Ryan & Deci, 2017).
	Number of students/apprentices in course meetings	Relatedness need (Ryan & Deci, 2017)
	Lectures attendance	Scoreboard (Quintas, 2019)
	Interest in the topic	Intrinsic motivation (Ryan & Deci, 2017), active processing (Mayer, 2014)
	Student's/apprentice's status of enrolment	Reinforcement principle (Skinner, 1953)
	Percentage of the students/apprentices that pass each subject	Diagnostic evaluation and personalization (Ausubel, 1968), scoreboard (Quintas, 2019).
	Number of credits obtained compared to the promotion of the students/apprentices	Competition, leaderboard (Quintas, 2019), Relatedness Principle (Ryan & Deci, 2017)
	Grades obtained	Reinforcement principle (Skinner, 1953), badges.
	Academic/VET performance	Competence Need (Ryan & Deci, 2017), progress.
	Absences	Scoreboard, active processing (Mayer, 2014)
	Special statuses	Identity, customing.

KPI	Data Fields	Theoretical foundation
Related to demographic indicators, personal - (AT-enrolment)	Student/apprentice's personal data (previous education, number of points in Grades 7.8 and 9, academic/VET record)	Diagnostic evaluation and personalization (Ausubel, 1968).

After, a second way of organizing these KPI is in function of the Model as in Table 2.

Table 2 - Model segmented KPI

MODEL	KPI	Data Fields
Personalised Tutoring	Individual Competences	Knowledge of the subject
		Use of digital media
		Achieve learning objectives
		Watching videos (Content consumption)
		Participation in forums
		Timeline of work
		Participation in videoconferences
		Gap in student/apprentice competencies from initial to target level
	Individual progress	Average mark (in real time)
		Percentage of the competences acquired in real time compared to the target competences
		Attendance to the sessions
		Percentage of completed assignments
		Date of submission of the various assignments
	Topic relevance	Feedback and evaluations
		Popularity of the content/subject

MODEL	KPI	Data Fields
		Number of students/apprentices in course meetings
		Lectures attendance
		Interest in the topic
		Student's/apprentice's status of enrolment
		Percentage of the students/apprentices that pass each subject
		Number of credits obtained compared to the promotion of the students/apprentices
		Grades obtained
		Academic/VET performance
		Special statuses
Active Learning	Diagnostic Evaluation	Percentage of the students that pass each subject
	Individual competences	Use of digital media
		Achieve learning objectives
		Watching videos
		Participation in forums
		Timeline of work
		Participation in videoconferences
	Individual progress	Average mark (in real time)
		Percentage of the competences acquired in real time compared to the target competences
		Attendance to the sessions
		Percentage of completed assignments

MODEL	KPI	Data Fields
		Date of submission of the various assignments
		Average mark (in real time)
	Topic relevance	Number of students/apprentices in course meetings
		Lectures attendance
		Student's/apprentice`s status of enrolment
		Number of years since last official course
		Feedback and evaluations
		Number of credits obtained compared to the promotion of the students/apprentices
		Grades obtained
		Academic/VET performance
		Absences
		Special statuses
Dropout Prevention	Diagnostic Evaluation	Previous courses
		Number of years since last official course
		Student's/apprentice`s interests
	Individual Progress	Gap in student/apprentice competencies from initial to target level
	Topic Relevance	Popularity
		Interest in the topic
	AT - Enrolment	Student's/apprentice`s personal data (previous education, number of points in Grades 7.8 and 9, academic/VET record)

These are simply two possible taxonomies for the KPI being the importance of them in the theoretical foundation showed in Table 1.

4 Selected data fields to monitor identified KPIs

Once the partners acknowledged which will be the various sets of potential data fields that they are capable to obtain, the relevance of the data fields and other aspects related were collected in Table 3.

Each data field, following scientific evidence, has been evaluated. The meaning of the columns is described below:

- Level of definition (1: low, 2: adequate, 3: good). Scale of quantitative estimation of how the data field is defined in a complete, exclusive, univocal and clear way. Data fields with 2 or 3 values are considered good for the model.
- Level of data collection (1: low, 2: adequate, 3: good). Quantitative estimation scale to assess how precisely the understanding of each data field is specified. Data fileds with 2 or 3 values are considered good for the model.
- Comments. Explanations about particular aspects of the data field how to improve it, etc.

Relevance (yes/no). Final decision about the relevance of the data field for the AI model.

Table 3 - Data field explanation

Data Field	DATA SOURCE (MOODLE, teams, etc.)	HOW	FREQUENCY	Level of definition (1-3)	Level of data collection (1-3)	Comments	Relevant for the application
Knowledge of the subject	Assignments	In the marks of the different tasks, we can see how much he knows about the subject.	It is updated every time a grade is entered.	3	3	It is a part of learning outcomes.	Yes
Use of digital media	Content Consumed, Forms	Digitally accessed contentment can be tracked, but it would also be interesting to know if the students like or dislike the content through survey forms.	Tracking of the used content is updated every time a user views a content. The form could be submitted once a month.	2	2	To be defined exactly what is “digital content”: videos, chat, web links. It is better not to send forms. People get tired about it.	Yes

Number of students/apprentices in course meetings	Enrolments (Attendance grid)	Look at number of enrolments.	Every time enrolments are completed. Usually once a year.	3	2	More frequently than once a year	Yes
Lectures attendance	Attendance Activities (Attendance grid)	Use assistance activities offered the digital platform.	Every time there is a lesson.	2	2	It is relevant, although the level of data collection needs to be better defined.	Yes
Interest in the topic	Forms	Forms to find out if the content is interesting.	The form could be submitted once a month.	3	2	The forms will need to be specific in order to collect students interests. It should be possible to add a small scale of estimation of each content with from 1 to 5 the degree of interest of the activity or content	Yes
Student's/apprentice`s status of enrolment	Enrolments (Academic/ VET office)	Look at enrolments.	Once a year, when enrolments are completed.	3	3		Yes
Previous courses	User Info – Student's previous course grades (last year): - Entrance exam.	In custom fields offered can be stored the type of subjects studied before.	Once, at the beginning of the training.	3	3	Entrance exam. Average qualification. - Baccalaureate. Average qualification. - Vocational training. These studies coincide with those applied for in the first place. - Other degrees.	Yes

	- Baccalaureate. - Vocational training. - Other degrees. - Other courses (continuing education).					Open question. - Other courses (continuing education). Open question. - Vocational values. Questionnaire by Cano, Orejudo and Cortés.	
Number of years since last official course	User Info - Year in which the student finished the last official course.	In custom fields offered can be stored the information related to when the last course was performed.	Once, at the beginning of the training.				Not
Student's interests	User Info – Ad hoc questionnaire.	In the custom fields offered by the digital platform	Once, at the beginning of the training. The student will have the opportunity to change it whenever they want.	3	3		Yes
Gap in student competencies from initial to target level	Assignments	With the passed assignments,	Every time a new assignment is carried out and graded.	2	2	Good definition of competences assigned to the level.	Yes
Percentage of the students/apprentices that pass each subject	Assignments	It can be obtained from grades.	Every time a course is finalised and graded.	3	3		Yes
Number of credits obtained compared to the promotion of the students/apprentices	Assignments	It can be obtained from grades.	Once a year, when final grades are uploaded.	3	3		Yes

Average mark (in real time)	Assignments	It can be obtained from grades.	Every time a course is finalised and graded.			Equal to the first data field. It could be used to obtain a different information by changing the variable.	See comments
Percentage of the competences acquired in real time compared to the target competences	Assignments	With passed assignments you can see what competencies you have obtained.	Every time a course is finalised and graded.				Yes
Attendance to the sessions	Attendance Activities	Use assistance activities offered by digital platforms	Every time there is a lesson.	3	3		Yes
Percentage of completed assignments	Assignments	It can be obtained from marks.	Every time an assignment is finalised and graded.	3	3		Yes
Date of submission of the various assignments	Assignments - Actual date of delivery by students.	It can be obtained from marks.	Every time an assignment is finalised and graded.	3	3		Yes
Feedback and evaluations	Assignments	It can be obtained from marks.	Every time an assignment is finalised and graded.	3	3	It is important to understand the feedback here is qualitative.	Yes
Student's/apprentice`s personal data (previous education, number of points in Grades 7.8 and 9, academic/VET record)	User Info	In the custom fields offered you can store what type of training you have studied previously.	Once, at the beginning of the training.			Previously asked. Maybe can be removed or use to obtain a different variable.	See comment
Achieve learning objectives	Assignments	With the passed assignments, you can see what competencies you have obtained.	Every time an assignment is finalised and graded.	2	2	Previously asked. Maybe can be removed or use to obtain a different variable.	See comment

Watching videos	Content Consumed	Digital platform stores the contents consumed by students/apprentices.	Every time a user consumes a content.	3	3	Previously asked. Maybe can be removed or use to obtain a different variable.	See comment
Participation in forums	Forums	Digital platform stores information about the forums and posts in these forums.	Every time a user participates in a forum.	3	3	Previously asked. Maybe can be removed or use to obtain a different variable.	See comment
Participation in videoconferences	Attendance Activities	Use assistance activities offered by Digital platform.	Every time there is a videoconference.	3	3	Previously asked. Maybe can be removed or use to obtain a different variable.	See comment
Grades obtained	Assignments	Can be obtained from digital platform marks.	Every time an assignment is finalised and graded.	3	3		Yes
Academic/VET performance	Assignments	Can be obtained from digital platform marks.	Every time an assignment is finalised and graded.	3	3		Yes
Absences	Attendance Activities	Use support activities provided by digital platform.	Every time there is a lesson.	3	3		Yes
Special statuses	User Info	In the custom fields offered by Digital platform you can store if the student has any special needs.	Once, at the beginning of the training. The student will have the opportunity to change it whenever they want.	3	3		Yes

5 Conclusions

As a conclusion we can state that academic/VET dropout poses a significant challenge in educational institutions worldwide, affecting the academic/VET progress and future prospects of students/apprentices. This project aims to explore how education processes could use AI to tutorize students / apprentices to avoid dropout and to achieve goals and targets in their training process. So, a very initial step is to define indicators associated with academic/VET dropout and career path. This KPI are based on a solid theoretical framework and have to be proved empirically as well as use according to regulations and laws in force in every country.

First of all, it has been necessary to build upon scientific theories to achieve this objective. As a result, the CTML and SDT theories have been proposed as suitable, compatible, and scientifically proven frameworks to support the fundamental principles of learning and teaching. These theories are in line with classical antecedents such as behaviourism, cognitivism, and constructivism. Subsequently, gamification has been presented and justified as a theoretical-practical model that effectively operationalizes these theoretical principles and translates them into concrete technical decisions in AI driven design. Additionally, learning principles derived from any interactive audiovisual activity have been taken into consideration. Each of the KPIs included has been previously extracted from some theoretical, teaching or learning principle.

By leveraging AI-driven interventions and personalized support systems, educational institutions can proactively identify at-risk students/apprentices, provide targeted interventions, and foster student/apprentice success.

Socioeconomic Factors:

Socioeconomic factors, such as low family income, limited access to resources, and financial burdens, contribute to academic/VET dropout. AI can assist in addressing these challenges by analysing large datasets to identify students/apprentices from economically disadvantaged backgrounds. By offering personalized financial aid information, scholarship opportunities, and career guidance, AI-powered systems can empower students/apprentices to overcome socioeconomic barriers and persist in their education.

Poor Academic/VET Performance:

Students/apprentices with consistently poor academic/VET performance often become disengaged and are at higher risk of dropping out. AI can play a crucial role in identifying struggling students/apprentices by analysing academic/VET data, assessing performance trends, and detecting early signs of academic/VET decline. With this knowledge, AI can recommend personalized interventions, adaptive learning materials, and tailored support to address specific academic/VET challenges, thereby increasing student/apprentice motivation and reducing dropout rates.

Lack of Individualized Support:

Limited access to individualized support and guidance can lead to feelings of isolation and frustration, increasing the likelihood of academic/VET dropout. AI-powered chatbots and virtual assistants can provide round-the-clock support, answering student/apprentice queries, offering academic/VET resources, and delivering personalized recommendations. These intelligent systems can simulate human interaction, offering a sense of connection and support to students/apprentices, regardless of their location or time constraints.

Inadequate Student/apprentice Engagement:

A lack of student/apprentice engagement can contribute to academic/VET disinterest and eventual dropout. AI can address this issue by leveraging data analytics to identify patterns of disengagement, such as irregular attendance, low participation, or limited interaction with course materials. AI-powered platforms can then provide tailored interventions, such as gamified learning experiences, interactive content, and real-time feedback, to enhance student/apprentice engagement and foster a positive learning environment.

Mental Health Challenges:

Mental health issues, including stress, anxiety, and depression, significantly impact student/apprentice well-being and academic/VET performance, often leading to dropout. AI can assist in early detection of mental health concerns by analysing student/apprentice behaviour, sentiment analysis of written assignments, or monitoring social media activity. AI-driven systems can then provide proactive support through mental health resources, counselling referrals, and personalized well-being programs to help students/apprentices cope with their challenges and persist in their education.

In conclusion, academic/VET dropout is a multifaceted issue influenced by various indicators. By harnessing the potential of artificial intelligence, educational institutions can take proactive measures to identify at-risk students/apprentices, provide personalized support, and address the underlying factors contributing to dropout rates. AI-powered interventions offer opportunities for targeted interventions, adaptive learning, round-the-clock support, enhanced student/apprentice engagement, and mental health assistance. By leveraging AI, educational institutions can create a supportive and inclusive environment, reducing academic/VET dropout and fostering student/apprentice success.

To attend this and create a personalized and proactive learning system, several KPI were chosen. In general, the KPIs chosen are aligned with the aim of the project and covered all the aspects related with the engagement of the student/apprentice and the previous background.

The selection of these KPIs is based on a triple procedure: on the one hand, a solid theoretical foundation has been built, related to evidence-based theories of education (learning and teaching), and supported by a broad scientific background. This foundation has been connected to the gamification model, serving as a design proposal for KPIs. It effectively bridges the gap between theoretical principles and technical decisions

Secondly, the knowledge of experts in the educational field, with theoretical and empirical knowledge about the conditions of learning success. The joint construction of the KPIs supports their suitability and has a theoretical justification, as discussed above. Finally, their selection has a second criterion of interest for this project. In order to arrive at them, the criterion of operationalization and feasibility for their collection among the different partners of this project has been taken into account. These three conditions together provide validity to the selection, in its conceptual and feasibility aspects. In addition, this approach may provide an opportunity to validate the proposed model, i.e., to have data collected through AI to validate at different times that the proposed model works properly.

6 References

Ausubel, D. (1960). The use of advance organizers in the learning and retention of meaningful verbal material. *Journal of Educational Psychology*, *51*, 267-272.

Ausubel, D. P. (1968). *Educational Psychology: A Cognitive View*. Holt, Rinehart & Winston.

Baddeley, A. D. (1999). *Human memory*. Allyn & Bacon.

Chiu, T. K. F., & Chai, C. S. (2020). Sustainable Curriculum Planning for Artificial Intelligence Education: A Self-determination Theory Perspective. *Sustainability*, *12*(14), Article 5568. https://doi.org/10.3390/su12145568

Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: the state of the field. *International Journal of Educational Technology in Higher Education*, *20*(1), 22. https://doi.org/10.1186/s41239-023-00392-8

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011). From game design elements to gamefulness: defining "gamification". 15th International Academic MindTrek Conference: Envisioning Future Media Environments New York.

Dewey, J. (1897). My Pedagogic Creed. *School Journal, 54*, 77-80.

Haleem, A., Javaid, M., Qadri, M. A., & Suman, R. (2022). Understanding the role of digital technologies in education: A review. *Sustainable Operations and Computers*, *3*, 275-285. https://doi.org/https://doi.org/10.1016/j.susoc.2022.05.004

Huang, X. X., Dong, L. H., & Vignesh, C. C. (2022). Self-Regulated Learning and Scientific Research Using Artificial Intelligence for Higher Education Systems. *International Journal of Technology and Human Interaction*, *18*(7), 15-15. https://doi.org/10.4018/ijthi.306226

Fu, X. R., Krishna, K. L., & Sabitha, R. (2022). Artificial Intelligence Applications with e-Learning System for China's Higher Education Platform. *Journal of Interconnection Networks*, *22*(SUPP02), Article 2143016. https://doi.org/10.1142/s0219265921430167

Gamulin, J., Gamulin, O. & Kermek, D. (2014). Comparing classification models in the final exam performance prediction. In *Proceedings of the 37th IEEE International Convention on Information and Communication Technology, Electronics and Microelectronics* (MIPRO), 663–668.

Gee, J. P. (2003). *What video games have to teach us about learning and literacy*. Palgrave Macmillan.

Jozsa, G., Oo, T. Z., Amukune, S., & Jozsa, K. (2022). Predictors of the Intention of Learning in Higher Education: Motivation, Self-Handicapping, Executive Function, Parents' Education and School Achievement. *Education Sciences*, *12*(12), Article 906. https://doi.org/10.3390/educsci12120906

Kapp, K. M. (2012). *The gamification of learning and instruction: game-based methods and strategies of training and education*. Pfeiffer.

Karyotaki, M., & Drigas, A. (2015). Online and other ICT Applications for Cognitive Training and Assessment. *International Journal of Online Engineering*, *11*(2), 36-42. https://doi.org/10.3991/ijoe.v11i2.4360

Lameras, P., & Arnab, S. (2022). Power to the Teachers: An Exploratory Review on Artificial Intelligence in Education. Information, 13(1). https://doi.org/10.3390/info13010014

Li, Q. Y., Duffy, P., & Zhang, Z. Y. (2022). A Novel Multi-Dimensional Analysis Approach to Teaching and Learning Analytics in Higher Education. *Systems*, *10*(4), Article 96. https://doi.org/10.3390/systems10040096

López-Zambrano, J. (2021). *Generic models for predicting final marks starting from the students' interaction information in Moodle*. Tesis Doctoral: UCO.

Mayer, R. E. (2011). *Applying the Science of Learning*. Pearson Education, Inc.

Mayer, R. E. (2014). *Cognitive Theory of Multimedia Learning in the Cambridge handbook of multimedia learning*. Cambridge University Press.

Mayer, R. E. (2009). *Multimedia learning*. Cambridge University Press.

Miller, G. (1956). The magic numer seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review, 63,* 81-97.

Paivio, A. (1986). *Mental representations: A dual-coding approach*. England: Oxford University Press.

Piaget, J. (2001). *The Psychology of Intelligence*. Routledge Classics.

Quintas, A. (2019). *Educational theory on technology, games and resources in didactics of early childhood education*. Prensas de la Universidad de Zaragoza. https://acortar.link/xlKZyS

Quintas, A. (2022). *Analyzing educational technology and gamification. An experimental approach*. Octaedro. https://acortar.link/yJb0nU

Ryan, R. M., & Deci, E. L. (2017). *Self-determination theory: Basic psychological needs in motivation, development, and wellness.* Guilford Press.

Rieckmann, M. (2012). Future-oriented higher education: Which key competencies should be fostered through university teaching and learning? *Futures*, *44*(2), 127-135. https://doi.org/https://doi.org/10.1016/j.futures.2011.09.005

Sailer, M., Hense, J. U., Mayr, S. K., & Mandl, H. (2017). How gamification motivates: An experimental study of the effects of specific game design elements on psychological need satisfaction [Article]. *Computers in Human Behavior*, *69*, 371-380. https://doi.org/10.1016/j.chb.2016.12.033

Shanmugan, S., & Satterthwaite, T. D. (2016). Neural markers of the development of executive function: relevance for education. *Current Opinion in Behavioral Sciences*, *10*, 7-13. https://doi.org/10.1016/j.cobeha.2016.04.007

Skinner, B. F. (1953). *Science and human behavior*. Macmillan.

Snow, E. L., Jacovina, M. E., & McNamara, D. S. (2015, Jun 22-26). Promoting Metacognition Within a Game-Based Environment.*Lecture Notes in Artificial Intelligence* [Artificial intelligence in education, aied 2015]. 17th International Conference on Artificial Intelligence in Education (AIED), Univ Natl Educac Distancia, Madrid, SPAIN.

Tejedor, G., Segalàs, J., Barrón, Á., Fernández-Morilla, M., Fuertes, M. T., Ruiz-Morales, J., Hernández, À. (2019). Didactic Strategies to Promote Competencies in Sustainability. *Sustainability*, *11*(7), 2086. https://www.mdpi.com/2071-1050/11/7/2086

Whitehill, J., Mohan, K., Seaton, D., Rosen, Y. & Tingley, D. (2017). MOOC Dropout Prediction: How to Measure Accuracy? In *Proceedings of the Fourth Association for Computing Machinery on Learning @ Scale*. Cambridge.

Xia, Q., Chiu, T. K. F., Lee, M., Sanusi, I. T., Dai, Y., & Chai, C. S. (2022). A self-determination theory (SDT) design approach for inclusive and diverse artificial intelligence (AI) education. *Computers & Education*, *189*, Article 104582. https://doi.org/10.1016/j.compedu.2022.104582

Yu, L. C., Lee, C. W., Pan, H. I., Chou, C. Y., Chao, P. Y., Chen, Z. H., Tseng, S. F., Chan, C. L., & Lai, K. R. (2018). Improving early prediction of academic/VET failure using sentiment analysis on self-evaluated comments. *Journal of Computer Assisted Learning 34*, 358-365. https://doi.org/10.1111/jcal.12247