REVIEW OF THE STATUS OF RESEARCH IN AI AND EDUCATION

ROLEPL-AI

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Deliverable 2.1 – Version 1

Type of Activity		
IO	Intellectual Output	**X**
A	Project Management and Implementation	
M	Transnational Project Meeting	
E	Multiplier Event	

Nature of the deliverable		
	Feedback from participants	
	Direct effect on participants and project partners	
	Practical & reusable resources for the practitioners	
	Research material bringing forward the reflection in the sector	**X**
	Community building tools	
	Partnerships and Cooperation	
	Dissemination material	
	Organizational and working documents	

Dissemination Level		
PU	Public	**X**
CO	Confidential, only for members of the consortium (including the Commission Services)	

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This project aims at training soft skills remotely, by pushing the practice through the implementation of an AI-based simulation.

The project runs from September 1st, 2023, to August 31st, 2025 (24 months), it involves 5 partners (Manzalab, Manzavision and Inceptive, France; VUC Storstrøm, Denmark; Fachhochschule Dresden, Germany) and is coordinated by Manzalab.

List of participants

Participant No.	Participant organisation name	Acronym	Country
1 (coord)	Manzalab	MZL	France
2	Manzavision	MZV	France
3	Inceptive	ICV	France
4	VUC Storstrøm	VUC	Denmark
5	Fachhochschule Dresden	FHD	Germany

CONTENT

Abbreviations

[AI] Artificial Intelligence
[AIED] Artificial intelligence in Education
[ALTs] Advanced Learning Technologies
[FAtiMA] Fearnot AffecTIve Mind Architecture
[HOTS] Hotel Operations Tactics and Strategy
[LLM]Large Language Models
[ML] Machine Learning
[PSI] Population Stability Index
[TSD] Theory of Self Determination
[VET] Vocational Education and Training
[VLE] Virtual Learning Environment
[UX] User eXperience

1 INTRODUCTION

1.1 OVERVIEW

This deliverable aims to report on the results of the literature review conducted about the scientific state of the art on AI use in educational scenarios. This research includes studies on the design and effectiveness of AI in education as well as regarding the combination of AI learning with other learning modalities, such as asynchronous and digital learning. In addition, it analyses studies on how AI can support learning through the development of cognitive, emotional, social and communicative skills and also its ethical issues, side effects and rights for a responsible use of new technologies.

1.2 DELIVERABLE POSITIONING

D2.1 is based on the state of the art and partners experience gained with previous projects; it is developed at the beginning of the ROLEPL-AI project before any experimentation.

It is connected to task 2.3 "Recommendations for use of AI in education and ALTAI self-assessment" within work package 1, all tasks in work package 4 regarding the development of the application, and task 5.1 "Research plan" in work package 5 to conduct experimentations. It should be considered as part of a consistent approach that will be implemented in the project throughout several activities to (1) guide the design of the application and (2) provide framework and tools for the evaluation of ROLEPL-AI application's impact on the users.

At the conclusion of the project, we will be able to assess the outcomes of the project by comparing them to the initial conditions and recommendations.

1.3 LEARNING SOFT SKILLS WITH AI

Artificial Intelligence (AI) aims at emulating higher order human processes such as analysing visual, audio, and text inputs, but also reasoning, classifying, or advising. In terms of technology, it encompasses machine learning, natural language processing, computer vision, robotics, and expert systems (Boucher, 2020, Gevarter, 1983). This wide variety of applications has led it to become an increasingly integral part of the educational landscape, revolutionizing traditional teaching methods and reshaping the learning experience for students worldwide (Chen, L., 2020).

The recent advancements in AI technologies such as ChatGPT and DALL·E on top of an already existing ecosystem of Intelligent Tutoring Systems (ITSs) let the intersection of AI and education garner significant attention. In the past five years, there has been a surge in the development and implementation of AI-driven educational tools aimed at providing personalized learning experiences and enhancing student engagement (Dai & Ke, 2022). However, along with the proliferation of AI in education come critical questions regarding its ethical implications, efficacy, and impact on learning outcomes (Chaudhry & al., 2021).

Recent studies have indicated a notable trend among students, with approximately 50% of respondents reporting regular utilization of generative AI tools like ChatGPT in their academic pursuits (Shaw et al., 2023). This statistic underscores the growing reliance on AI-driven solutions to support and augment the learning process. While the integration of AI in education offers promising opportunities for innovation and efficiency, it also raises concerns regarding issues such as data privacy, algorithmic bias, and the erosion of critical thinking skills. Consequently, there is a pressing need for rigorous research and analysis to navigate the complex terrain of AI in education and its implications for pedagogy, curriculum design, and student learning experiences.

Against this backdrop, this report seeks to explore the multifaceted relationship between AI and education, focusing on the emergence of Artificial Intelligence in Education (AIED) as a pivotal concept in contemporary educational discourse. Drawing upon insights from cognitive psychology, educational theory, and technological innovation, we aim to elucidate the potential benefits and challenges associated with the integration of AI in educational settings. Specifically, we will delve into the impact of AI on learning processes, the acquisition of soft skills, and the development of AI literacy among students and educators.

Through a comprehensive literature review and empirical analysis, we will examine the role of AI-driven approaches in enhancing teaching and learning practices, as well as their implications for educational equity and accessibility. Additionally, we will explore their application to learning soft skills, which play a key role in the field of our project, the tourism industry. They have become increasingly important in elevating the quality of service, fostering teamwork, and effectively addressing challenges, enhancing guest experiences and satisfaction.

Ultimately, this report endeavours to contribute to the ongoing dialogue surrounding AI in education, offering insights and perspectives that can inform future research, policy development, and pedagogical practice in the digital age. By critically examining the opportunities and challenges presented by AI technologies, we hope to foster a deeper understanding of their transformative potential in shaping the future of education.

2 LEARNING: A COMPLEX COGNITIVE PROCESS

2.1 DEFINITION OF LEARNING

George (1990) offers a definition of learning as "the process of modifying knowledge, or modifying behaviour, during interactions of an organism (system) with its environment. Changes in knowledge must be evidenced by observable change, and [...] changes in behaviour can be attributed to changes in knowledge." This definition delineates learning as a selective process, wherein progress stems from an individual's interactions with their environment. It underscores the active role played by the learner, which is not only essential but also indispensable for effective learning outcomes.

Central to this definition is the concept of memorization, described as a cognitive process involving the encoding of various forms of knowledge (declarative and procedural) into long-term memory (Anderson, 1983, 1993, 1996). When discussing memorization, distinct phases must be identified: (1) information reception and processing, (2) encoding, and (3) retrieval.

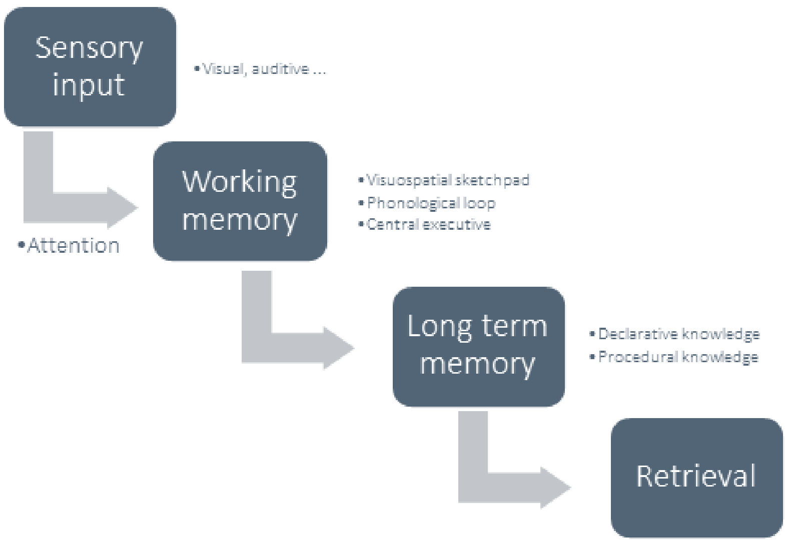

Figure 1: Different phases in the memorization process

The phase of reception and processing is defined as the working memory (Baddeley, 1992, 1996, 2012), formerly known as short-term memory (STM). The working memory represents an advancement from the STM model, proposing a three-component model for information processing: the visuospatial sketchpad (for temporary storage of visual and spatial information), the phonological loop (for temporary storage of verbal and pronounceable material), and the central executive (which coordinates the functions of the other two systems) (Baddeley, 1996).

During the encoding phase, information slated for retention is transferred to long-term memory (Anderson, 1996) through various learning strategies such as recall, re-reading, and help-seeking. Declarative knowledge (episodic and semantic) and procedural knowledge (know-how) are the two types of knowledge organized and stored.

The learning process may remain incomplete if the encoded knowledge is not retrieved. Information retrieval serves not only as a learning strategy but also as a means of self-assessment. Encoding always occurs within a specific context, which influences its impact. Actively engaging in retrieval not only deepens encoding but also introduces alternative contexts, thereby facilitating future retrieval.

This model of memorization and learning highlights the finite duration and capacity of working memory to retain information. Upon reception, information may or may not undergo processing within the working memory, and subsequently, it may or may not be transferred to long-term memory. These cognitive processes can be adversely influenced by various factors, including attention deficits, lack of motivation, or cognitive overload, resulting in disruptions to long-term memory storage.

Extensive research has underscored the advantages of fostering active engagement in learning to enhance attention and performance (Hake, 1998). Furthermore, studies by Redish (1997) and Laws (1999) have demonstrated that active learners demonstrate superior recall abilities compared to passive learners, consequently fostering greater student engagement.

While the benefits of learner agency in traditional classroom settings are well-documented, the efficacy of Virtual Learning Environments (VLEs) warrants exploration. Technologies such as virtual reality, mixed reality, or novel applications offer value through their interactive nature and provision of feedback within VLEs (Rose, 2000), which can be tailored to individual learners.

New technologies offer learners a platform where a significant level of control is vested in their hands. Active engagement within a VLE enables users to interact with it (Lourdeaux, 2001) and manage various aspects of their learning experience, including content selection, duration, and thematic focus. Consequently, learners can assume full agency in their learning journey, either by actively seeking out knowledge or by passively receiving and assimilating curated information.

Moreover, technologies such as VLEs and Artificial Intelligence (AI) can facilitate the retrieval of diverse types of knowledge within different contexts, thereby promoting deep encoding and contextualized learning experiences. Understanding how to leverage these emerging technologies necessitates a comprehensive understanding of the factors influencing learning processes, enabling educators to optimize VLEs and mitigate associated risks through the integration of these innovations.

2.1.1 Motivation and learning

Motivation plays a significant role in the realm of education (Fassbender, 2012), serving as a critical determinant of success (Ramaley, 2005) by fostering students' perseverance in their learning endeavours. Among the plethora of motivational theories, we have chosen to focus on one of the most prevalent: the Theory of Self-Determination (TSD), as formulated by Ryan and Deci (2000).

The TSD posits the existence of various types of motivation, namely intrinsic motivation, extrinsic motivation, and amotivation, which represents a complete lack of intention to act (Deci, 2000). Central to this theory is the concept of a continuum of motivation, wherein individuals may transition between the least self-determined forms of motivation to the most self-determined. This framework gives rise to a hierarchy of motivational regulations, delineating different levels of internalization, development, and refinement of individual structures and representations.

Individuals driven by intrinsic motivation operate under internal regulations, engaging in activities based on their personal choices, values, and perceptions (Deci, 2008). Motivated intrinsically, individuals undertake tasks for the inherent satisfaction they derive from them (Deci & Ryan, 2008). Such individuals exhibit a genuine interest in their activities, actively exploring challenges to facilitate deeper engagement with the subject matter and enhance their learning outcomes.

In contrast, extrinsic motivation arises when individuals engage in activities for external reasons, such as seeking rewards or avoiding punishment. Within the realm of extrinsic motivation, individuals exhibit varying degrees of integration of external incentives, which influence their engagement with the task at hand.

Individuals propelled by intrinsic (or autonomous) motivation demonstrate greater persistence compared to those motivated extrinsically (controlled), actively seeking to expand their knowledge acquisition driven by their personal aspirations. Consequently, autonomous intrinsic motivation is strongly associated with enhanced learning outcomes (Deci, 1991).

Moreover, autonomous regulation has been linked to improved academic outcomes (Black, 2000) and greater persistence in tasks (Pelletier, 1995), suggesting that learners with intrinsic or autonomous motivation tend to exhibit more effective learning behaviours.

To bolster intrinsic motivation, which remains a continuous factor, educators can employ various techniques and tools. Motivational deficits may stem from issues such as low self-esteem or unclear goal setting. Within the framework of self-determination theory (Ryan, 2017), researchers emphasize the significance of autonomy, perceived competence, and relatedness in fostering motivation.

Attending to these fundamental human needs is believed to enhance learners' motivation, thereby contributing to improved learning performance. The potential of new technologies such as AI is currently under scrutiny to ascertain their capacity to address these human needs and augment intrinsic motivation.

2.1.2 Cognitive load and learning

In literature, the concept of cognitive load is predominantly utilized within the domain of education and learning, whereas the concept of mental workload is currently gaining prominence in ergonomics and human factors, as discussed by Orru (2019).

The definition of cognitive load revolves around the utilization of working memory resources for a given task, a notion underscored by Baddeley (2012) and Leppink (2017). It is imperative to acknowledge the finite nature of these working memory resources, as emphasized by several authors (Adams, 2018; Camina, 2017; Chai, 2018).

Eriksson (2015) characterizes working memory as the capacity to retain information in an easily accessible state for brief durations, typically ranging from several seconds to minutes, to support ongoing tasks. This notion of the limited capacity of working memory resources aligns with the Multiple Resource Theory, posited by Basil (2012), which suggests that individuals possess a finite pool of mental resources allocated across various tasks, modalities, and cognitive processes, spanning from sensory-level to meaning-level operations.

Cognitive load is commonly categorized into three sources of mental load:

- Intrinsic load: This pertains to the inherent effort required for an activity, representing the inherent level of difficulty, such as the association of elements or comprehension of tasks.
- Extraneous load: This arises from the presentation of information, materials, devices, or design. This type of load can influence users' cognitive processing and is the only source of load that can be manipulated.
- Germane load: This involves the processing, construction, and automation of schemas, constituting mental effort aimed at fostering deeper understanding and skill acquisition.

A cognitive overload can occur when one or multiple sources of cognitive load become overwhelming. However, it is important to recognize that if cognitive load can be overstimulated, it can also be mitigated. The only source that cannot be reduced is the Germane load. When introducing new materials or technologies in a learning environment, it is critical to consider cognitive load to prevent overload. This can be achieved by allowing learners to explore the environment autonomously (Kirschner, 2006).

Cognitive overload can result from factors like task complexity, rapid information presentation, or simultaneous task processing. Designing tasks and information delivery to minimize cognitive overload is crucial for fostering effective learning.

Effective learning and problem-solving often require the management and optimization of cognitive load.

Educators and instructional designers should strive to present information and tasks in a manner that minimizes extraneous cognitive load. For example, applying Mayer's principle of multimedia learning (Clark, 2023) enables learners to concentrate on intrinsic cognitive load and allocate mental resources to meaningful learning and problem-solving processes. The objective is to achieve a balance between cognitive load and an individual's cognitive capacity, ensuring that tasks are challenging yet manageable.

2.1.3 Self-Regulation and learning

Self-regulation is defined as the deliberate use of strategies by an individual to achieve a goal (Bouffard-Bouchard, 1988), resulting in enhanced learning outcomes (Pintrich, 2000).

This author defines self-regulation as an active, conscious process put in place by the learner, enabling the construction of their knowledge while having control over this elaboration. Learners are no longer regarded as passive recipients of knowledge, but as individuals who can be active and co-construct their own knowledge, thus knowledge, which in turn promotes learning.

However, as self-regulation entails managing one's cognitive processes during learning, it is essential to implement strategies and behaviours that lead to self-regulation. Individuals must select which strategies to utilize, why they are chosen, and how to implement them. In his model, the author delineates four phases that individuals undergo when activating self-regulated learning.

1. Goal planning: Learning objectives are established at the outset of the learning phase, guided by motivation (cf. 2.1.1) and learners' initial knowledge of the subject. This process enables learners to form judgments about the ease of learning (Nelson, 1990) and plan the time and effort required to attain their learning objectives.
2. Cognitive monitoring: Also referred to as self-evaluation, it involves the surveillance of one's own cognition to manage effort (e.g., whether to continue the learning task) and allocate time effectively, by dedicating more time to learning tasks deemed difficult. Through this process, individuals assess their comprehension of the subject and evaluate acquired knowledge. This assessment of knowledge enables predictions regarding knowledge retention and confidence in retrieval (Nelson, 1990). The accuracy of cognitive monitoring significantly influences the subsequent phase, as individuals adjust their activity to bridge the gap between their current state of knowledge and the desired level.
3. Regulation: In this phase, the learner selects learning strategies based on previous monitoring, such as rereading, repetition, information retrieval, testing, seeking assistance, or transitioning to another topic. The choice of learning strategies is influenced not only by monitoring (accurate or

inaccurate) but also by the perceived cost of effort. At the conclusion of this phase, the metacognitive process of self-regulation can serve as a retroactive loop, facilitating the revision of goals based on evaluation (Puustinen, 2001).

4. Cognitive reaction and reflections: This phase occurs after the learning phase and involves evaluating learning performance, often accompanied by emotional reactions. The outcomes of this phase influence subsequent behaviour in future learning phases.

These phases are intricate, and learners may not always exhibit the appropriate behaviour. Deficiencies in self-regulation may stem from a lack of self-regulatory skills, necessitating assistance in implementation by adjusting contextual or individual factors.

New technologies are currently being explored to aid learners in self-regulation by offering virtual assistants or VLEs that facilitate self-assessment, or by suggesting corrective actions (Richards et al., 2009; Huet et al., 2016).

2.2 Hard skills and Soft skills

When defining learning, research in this field investigates the influence of various variables (motivation, cognitive load, self-regulation) on retention performance, assessing learners' ability to recall knowledge or execute tasks. Learning tests encompass two categories: "Hard skills" and "Soft skills."

Hard skills encompass technical abilities, comprising declarative and procedural knowledge, such as medical knowledge, quantifiable and applicable to specific tasks or situations.

Soft skills, as defined by Robes (2012), denote intangible, non-technical, personality-specific attributes, including emotional intelligence, adaptability, teamwork, and communication skills, recognized for their significant impact on individuals' personal and professional lives (Heckman and Kautz, 2012).

Educational and pedagogical practices are being tested to cultivate soft skills, with role-playing strategies emerging as the most commonly utilized approach (Schutt et al., 2017). Previous research, such as that conducted during the Erasmus+ project Hotel Academy, has demonstrated the positive impact of role-play training on soft skills development in Vocational Education and Training (VET) for the hospitality industry (Arnold, 2023).

The significance of soft skills is increasingly recognized in both work environments and educational settings. While AI research traditionally emphasizes procedural skills and declarative knowledge, contemporary studies are starting to focus on interpersonal skills.

3 Artificial Intelligence in Education

3.1 Definition

AI, as generally defined, is regarded as "machine intelligence demonstrated by non-living entities, contrasting with natural intelligence exhibited by humans and other living organisms" (Leahy, 2019).

Currently, AI encompasses the fields of machine learning, natural language processing, and the creation of intelligent programs and machines capable of addressing various problem types (Mondal, 2020).

The definition of AI proposed by the High-Level Expert Group on Artificial Intelligence appointed by the European Commission (HLEG) in 2019 is as follows::

"Artificial intelligence (AI) systems are software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal. AI systems can either use symbolic rules or learn a numeric model, and they can also adapt their behaviour by analysing how the environment is affected by their previous actions."

Nowadays, there are numerous definitions and applications of AI. In response to this diversity, major software companies in the field, including Google, Apple, and Microsoft, have established guidelines for development. Wright et al. (2022) analysed these guidelines and successfully categorized them into broad groups:

- Initial: This category pertains to considerations essential prior to development, such as the ethical value of AI, fairness, and privacy.
- Model: Guidelines in this category address various aspects of model development, including model categories and the design of machine learning models themselves.
- Deployment: This category encompasses considerations regarding model deployment and fine-tuning, including how feedback is collected and utilized, as well as how the system handles errors.
- Interface: Guidelines in this category focus on the design and interactions of the AI interface.

Figure 2: Unified guidelines from Apple, Google and Microsoft, in Wright & al. (2022)

The number of guidelines generated is substantial (160), and they are highly generalized, making them adaptable to various types of AI applications. However, while these guidelines primarily focus on AI software development, some offer insights into human-AI interaction. Yet, their precision depends on the specific purpose of the AI, its intended use, and its end-users.

Currently, following the interest of major corporations, attention to AI has surged in the educational sector due to its potential to enhance learning support (Hwang et al., 2020a). Artificial intelligence in education (AIED) represents a new frontier in AI impact research (Chen, 2020a). Within the educational domain, AI holds promise for assisting teaching by providing direct support to teachers or students. It serves as a predictive tool for teachers and as a support mechanism (e.g., recommendation systems, chatbots) and feedback provider (e.g., virtual agents) for learners (Su, 2023).

3.2 AI IN EDUCATION: AIED

Two primary areas of focus have emerged in current research on education and AI: Learning with AI and Learning about AI (Holmes, 2019). The former entails utilizing AI as a learning tool (e.g., AI agents, AI tutorials, AI-managed learning processes), while the latter involves comprehending AI's nature and functioning to facilitate learning through AI.

Termed AI literacy in the literature, the study of Learning about AI entails acquiring knowledge, understanding, and practical application of AI (Ng, 2021), rather than examining the impacts of AI application on users or learners. The importance of AI literacy lies in the belief that users can evaluate and self-regulate their AI utilization when they possess a comprehensive understanding of AI.

Currently, research primarily focuses on enhancing AI literacy regarding AI tools. However, future investigations may explore AI-simulated learning or AI agents and their effects on learning, particularly in contexts where users possess varying degrees of AI literacy.

The value of this report is to focus on the review of learning with AI, particularly its direct application as a learning tool and its consequential impact. The advancement of artificial intelligence introduces novel avenues for enriching the learning process.

Currently, significant conceptual exploration is underway to determine the potential applications of AI in learning. Mollick & Mollick (2023) propose a comprehensive list of AI applications:

(1) AI-tutor: Providing direct instructions

(2) AI-coach: Enhancing metacognition

(3) AI-mentor: Offering feedback
(4) AI-teammate: Fostering collaborative intelligence
(5) AI-simulator: Facilitating practice and hands-on experience
(6) AI-student: Assisting in teaching others

These various applications of AI are now starting to undergo examination, although research in this area is still nascent due to the rapid evolution of new possibilities in recent years. For instance, Dai & al. (2022) investigated AI for education (AIED) employing a virtual agent in simulated environments, which aimed at guiding and facilitating cognitive regulatory processes while contextualizing learning.

Studies are now beginning to explore the potential for integrating this technology into educational settings (Kim, 2022). AI offers the potential to develop programs that aggregate and analyze students' learning processes and performances. Consequently, personalized learning environments, parameters, and customized content and feedback can be envisaged to support student learning (Peng & al., 2019; Cho & al., 2019).

For instance, Chin & al. (2014) view AI as a conversational agent for learning, aiming to support students' cognitive development. Utilizing AI as an empathic peer or tutor agent can enhance learning interest, motivation, and self-regulation. Similarly, Markauskaite & al. (2022) regard AI as AI-driven scaffolds, analyzing learners' activities to offer feedback and guidance in self-regulated activities. Additionally, some researchers explore the application of AI in simulation-based learning environments (Chen & al., 2020; Dai & Ke, 2022; Johnson & Lester, 2016).

It's noteworthy that a segment of research investigating AI as a learning tool adopts the theory of distributed cognition (Kim, Lee & Cho, 2021), which offers insight into cognitive processes in relation to the environment and interactions (Hutchins, 1995), positioning AI within these cognitive processes. Regarding students' interaction with AI, research suggests three types of interactions:

- Cognitive interaction involves interactions concerning the content or learning process (Dillenbourg, 1995; Hmelo-Silver, 2008).
- Socio-emotional interactions pertain to the socio-emotional climate fostered by interactions with AI, which can influence learning outcomes.
- Artifact-mediated interaction examines how the design of the AI interface can affect learners and their learning.

This conceptual framework provides considerations for how AI can be integrated into education, its potential impact, and the design of AI in educational settings.

In recent years, there has been a growing interest in utilizing AI in education (AIED) for fostering the development of non-epistemic competence components (Joksimovic et al., 2020), such as metacognition and self-regulated learning

(Azevedo et al., 2019), emotion (Harley et al., 2017), social interaction skills (Porayska-Pomsta et al., 2018), and motivation (du Boulay, 2018).

3.2.1 AI and the cognitive interaction

In a prior investigation, Lin (2021) discovered that an environment featuring AI interaction had yielded a positive influence on students' cognitive processes such as problem-solving, logical thinking, and collaboration. Additionally, AI can serve learners in enhancing their metacognitive processes, including asking questions or self-assessing their learning (Chaudhry & al., 2021; Markauskaite & al., 2022).

AI for Metacognitive process

For instance, Fu & al. (2020) emphasized that AI equipped with automatic responses and feedback can offer assistance to learners who may hesitate to ask questions to instructors in traditional learning settings. Similarly, Kim & al. (2022) suggested employing AI as a collaborative learning agent in classrooms, where students interact with AI to collaborate in their learning environment, mimicking peer-to-peer assistance and feedback. In these investigations, learners are depicted as active participants in their learning and interaction with AI, rather than passive recipients guided by AI.

Active involvement in the learning process has been shown to enhance engagement, learning performance, and long-term knowledge retention compared to passive receipt of information by learners (De Freitas, 2015; Hamari, 2016; Xie, 2019). This active role of learners in AI-supported learning environments appears crucial for the effectiveness of such environments. However, there remains a dearth of studies comparing passive and active learning with AI in the current literature.

Moreover, with the aim of enhancing cognitive processes by supporting teachers, Nazaretsky & al. (2022) developed an AI algorithm for their research that provides teachers with learning analyses of their students, grouping them based on competency skills and assisting teachers in delivering personalized instructions tailored to each group's learning needs. Their study concluded that this collaboratively developed AI algorithm for learning science aids teachers in offering adapted instructions that align with the modern science classroom in blended learning settings.

Research on cognitive and metacognitive processes predominantly positions AI as a diagnostic tool to enhance the provision of tailored feedback, either by teachers or AI agents. This feedback is crucial for learning performance as it directly influences learners' pursuit of their learning goals (Deci & Ryan, 2008).

Studies indicate that users employ different learning strategies based on their motivation levels (Rashid, 2019), with higher levels of intrinsic motivation positively linked to the appropriate use of learning strategies. Recent investigations on Chatbot-based learning suggest that it fosters student motivation, particularly intrinsic motivation (Fryer & al., 2019; Yin & al., 2021; Chiu & al., 2023).

Furthermore, Huang & al. (2023) conducted research on an AI system designed to stimulate intrinsic motivation. Their findings revealed that AI-driven personalized video recommendations for learners not only enhanced their learning performance but also increased their engagement and motivation levels to learn.

AI and Cognitive load

Discussing AI and cognitive interaction inevitably involves addressing the cognitive (over)load it may induce. Luo & al. (2020) conducted three experiments utilizing AI coaches to train job skills for sales agents. Their initial experiment revealed varying benefits provided by AI coaches compared to human managers, following a U-shaped pattern among agents. While some agents experienced significant performance improvements, others demonstrated limited additional progress, attributed to an overload of information from AI coaches compared to human coaches. Subsequent studies found that the most effective training approach involved a combination of AI and human coaches. Human coaches assisted users in managing information overload or excessive input.

Such overload is frequently encountered in e-learning training and can be mitigated by aligning multimedia training with learners' cognitive processes, adhering to guidelines from multimedia theory (Mayer, 2017). Grounded in cognitive load theory (Sweller, 2011), these guidelines aim to prevent extrinsic (material-induced) cognitive overload by adjusting to cognitive processes. Adherence to these guidelines can mitigate the risk of cognitive overload (Mayer, 2017), thereby enhancing cognitive processes (refer to Table 1).

Although no research directly addresses the efficacy of these requirements in AI-based environments and learning performance, studies on e-learning or immersive environments in computer and virtual reality contexts have demonstrated a reduction in cognitive load by adhering to these principles (Makransky & al., 2017; Moreno & Mayer, 2000). Prioritizing the avoidance of cognitive overload in learners when utilizing AI is essential, achieved through utilizing AI as a tool (offering adapted lessons) or employing AI agents that adhere to these guidelines (utilizing human voices, pre-training, etc.).

Table 1 Mayers' Guidelines

Category	Name	What to do
Reduce extraneous process	Coherence	Extraneous material (non-directly linked to the learning) has to be excluded
	Signalling	Essential material is highlighted
	Redundancy	Graphic and narration bring more learning than graphic, narration and on-screen text
	Spatial contiguity	On-screen words are placed next to the corresponding part of the graphic
	Temporal contiguity	Corresponding narration and graphic are presented simultaneously
Manage	Segmenting	Present lesson in small user-paced segments

essential process	Pre-training	Key terms need to be known before the lesson
	Modality	Words are presented in spoken form
Foster generative process	Personalization	Present the words in a multi-media lesson in conversational style rather than formal style
	Voice	Human voice is better for learning performance than machine-like voice
	Embodiment	On-screen agent should use human-like gesture and movement

3.2.2 AI & socio-emotional interactions

Emotions

Emotions are recognized today as having a significant impact on learning performance, particularly positive emotions (Harley & al., 2017; Tuomi, 2022). The field of study focusing on inducing positive emotions through Advanced Learning Technologies (ALTs) aims to develop emotion-aware systems (D'Mello and Graesser, 2015).

Hwang (2020) demonstrated in their study that anxiety related to a learning subject could be mitigated through the implementation of AI, utilizing emotion and cognitive performance analysis to provide feedback. Similarly, McLaren (2011) observed enhanced learning performance in the context of interactions with a polite web-based tutor compared to regular web-based tutors.

Emotionally engaging learners is crucial as it involves affective arousal and fosters emotional bonds within learning contexts (Mollen, 2010). Research indicates that when emotional engagement is positive, characterized by feelings such as curiosity and enjoyment, dropout rates decrease, and learning achievement improves (Kim, 2014).

Using an AI-virtual agent in a VLE also enables users, such as teachers, to interact with virtual students. Dai & al. (2021) received feedback indicating that their AI-virtual agent, in this case, a virtual student reacting negatively to the instructor, facilitated the simulation of challenging situations. Although they did not assess the learning outcomes of these interactions, the seamless simulation was well-received by instructors, suggesting potential for further experimentation.

Furthermore, it's noteworthy that learners' attitudes, emotions, and perceptions toward the source of learning, such as social robots, can significantly impact learning performance. Spatola & al. (2021) found that learners achieved higher performance when receiving help from a human source compared to a robot source, particularly when attitudes towards robots were negative or less positive than towards humans. Therefore, understanding attitudes towards technology and providing human-like agents or voices can positively impact learning performance using AI.

To induce positive emotions in ALTs, Harley & al. (2017) propose a taxonomy. They suggest a proactive approach by intentionally inducing positive emotions and a reactive approach by monitoring negative emotions. Positive emotion induction can be achieved through a User Experience (UX) approach, constructing a positive environment based on models like the multimedia learning theory (Mayer, 2017) discussed previously. Meanwhile, emotion monitoring involves systems analyzing various variables such as negative verbalizations, indicators of cognitive overload (e.g., EEG, lack of attention, eye tracking), and learning performance. These dual approaches aim to offer adaptable technology (Figure 3) capable of inducing positive emotions based on user states.

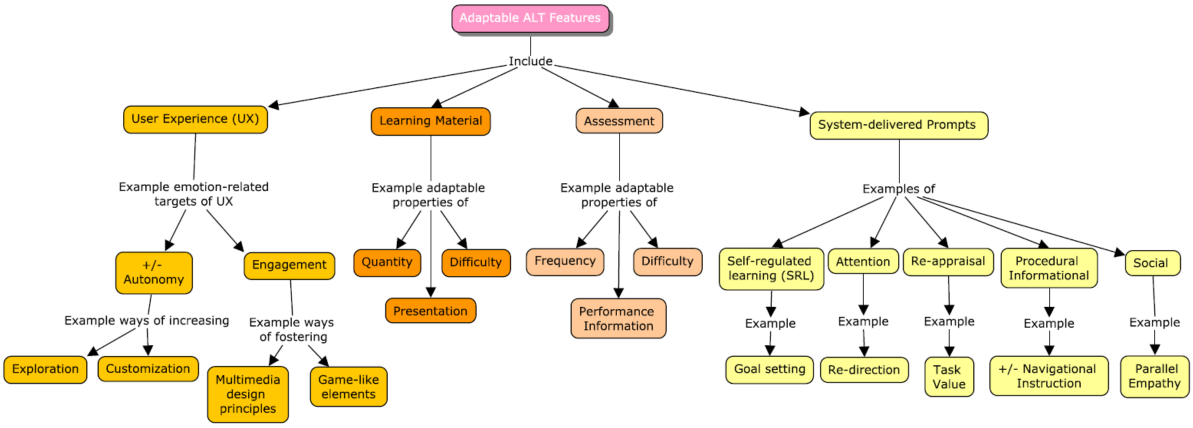

Figure 3: Adaptable ALT features by Harley & al. (2017)

This taxonomy provides insights into implementing emotionally aware systems, potentially leading to positive impacts on learning outcomes.

In the realm of research on aware systems, Mascarenhas & al. (2022) have developed a toolkit for constructing virtual characters with social and emotional intelligence. Built upon the Population Stability Index (PSI) model, a cognitive motivation-based theory proposed by Bach & al. (2009), this toolkit, named FAtiMA (Fearnot AffecTIve Mind Architecture), has demonstrated effectiveness in assisting users with their tasks. Although the FAtiMA-based AI agent has not yet been tested in the context of learning, examining its architecture could inform future developments or even be applied in educational studies given its open-source nature.

Soft skills competences

AI interactions can play a mediating role in learning, exerting a non-direct influence on factors such as emotion, which in turn affect learning outcomes.

However, AI interactions can also directly impact learning, particularly in the development of socio-emotional skills, commonly referred to as soft skills. The heightened interest in soft skills today can be attributed to concerns about the potential replacement of technical and repetitive jobs by technology (Murcio & al., 2021), thereby emphasizing the importance of human-centered relationship aspects. Consequently, there is a growing demand for humanity and the cultivation of soft skills necessary for effective interaction management.

Soft skills are acknowledged to be adaptable and trainable (Borghans & al., 2008; Chernyshenko et al., 2018), making them amenable to improvement through training. Schutt & al. (2017) investigated AI-based simulation (vPlay system) training aimed at enhancing soft skills among healthcare trainees. Their findings indicate that the vPlay system positively influenced trainees' perception of confidence in their ability to safely administer medication to patients. It's noteworthy that their evaluation was based on trainees' perceptions rather than direct observations of their performance on the job.

In the healthcare domain, there's a recognized need to enhance team communication skills (Lancaster et al., 2015; Chua et al., 2020). To address this, researchers have investigated the impact of simulation-based training on soft skills. For instance, Liaw & al. (2023) demonstrated a significant improvement in communication knowledge and self-efficacy scores following AI-based simulation training.

Their simulation involved a 3D VR game where users assume roles as doctors or nurses engaging in team communication during transitions, allowing them to assess the consequences of effective information transmission. Through this AI-based simulation, participants acquire new communication skills.

Stamer & al. (2016) conducted a review on the role of AI in supporting communication skills development in healthcare education. They identified the practicality and potential effectiveness of generating natural language within simulated virtual interactions between patients and healthcare providers. Additionally, they noted the promising prospects of AI- and ML-driven analyses of language and speech for providing feedback to learners.

Soft skills are increasingly valued across various industries, not limited to healthcare but also encompassing public-facing sectors like hospitality or sales (Murcio & al., 2021). However, there's a notable dearth of research in this area. Nonetheless, simulation-based training for soft skills is gaining traction and is acknowledged for its positive impact on skill mastery (Douglas, Miller, Kwansa, & Cummings, 2008; Mitchell, 2004).

Simulations are proven effective instructional tools that complement traditional classroom learning, fostering student engagement and transforming them into active participants in the learning process (Singh, Mangalaraj, & Taneja, 2010). By replicating the characteristics, features, and appearance of real systems, simulations enhance learning outcomes (Render, Stair, & Hanna, 2006).

Present research on soft skills primarily focuses on medical education (Stamer & al., 2023) and hospitality (Pratt & Hahn, 2016). In the hospitality sector, studies indicate that simulation-based learning and case studies cultivate essential competencies for students in hotel management (Ineson, Rhoden & Alexieva, 2011). However, empirical research in Hotel Operations Tactics and Strategy (HOTS) remains scarce, as noted by Pratt & Hahn (2016).

Hospitality and simulated training were explored in a previous Erasmus+ project called Hotel Academy (2019–2021), aimed at designing a shared curriculum to facilitate virtual collaboration among three European universities in Cyprus, France, and Germany. A VLE application was developed, featuring both desktop and VR-based scenarios, enabling students and faculty members to engage in roleplay scenarios addressing authentic professional challenges rooted in complex, realistic life events.

The primary aim of the simulation was to foster collaboration, communication, strategic thinking, and problem- and conflict-solving skills (Arnold, 2023). Participant feedback was generally positive, highlighting the scenarios' potential and positive aspects. Students were able to develop strategic competencies that enhance both their professional and personal growth.

3.2.3 Mediation of interaction with AI

Considering human-new technology interactions involves developing these technologies with a human-centred approach. Current research on AI-interaction design examines traditional user interface design guidelines.

For instance, Nielson's heuristics (1990, 1992) proposed 10 guidelines for designing a user-centred interface:

1. Visibility of system status
2. Match between system and the real world
3. User control and freedom
4. Consistency and standards
5. Error prevention
6. Recognition rather than recall
7. Flexibility and efficiency of use
8. Aesthetic and minimalist design
9. Help users recognize, diagnose, and recover from errors
10. Help and documentation

Some of these guidelines can be applied to guide the development of AI interfaces. However, Amershi & al. (2021) suggest that AI interfaces may conflict with some of these guidelines due to the nature of the technology itself. They use the consistency principle as an example, noting that AI interfaces may struggle to adhere to this principle due to their evolving nature and personalized responses and experiences.

As the issue of inaccurate interface guidelines is recognized within the research domain of AI-interface, new studies have been undertaken. For instance, Fu & al. (2020) demonstrate that the accuracy of AI speech recognition and the social presence of the AI impact the continued use of AI and interaction with it.

The authors partially based their research on the affordance theory (Dalgarno & al., 2010), which outlines the affordance requirement of 3D VLEs that enhance users' satisfaction and usage. This requirement, which involves accurate and speedy speech recognition to improve social presence during learning, could inform the development of AI environments for learning. Similarly, Jung & al. (2018) recently discovered an effect of engagement between presence and learning persistence.

Table 2 Human-AI interaction design guideline by Amarshi & al. (2022)

	AI Design Guidelines		Example Applications of Guidelines
Initially	G1	**Make clear what the system can do.** Help the user understand what the AI system is capable of doing.	[Activity Trackers, Product #1] "Displays all the metrics that it tracks and explains how. Metrics include movement metrics such as steps, distance traveled, length of time exercised, and all-day calorie burn, for a day."
	G2	**Make clear how well the system can do what it can do.** Help the user understand how often the AI system may make mistakes.	[Music Recommenders, Product #1] "A little bit of hedging language: 'we think you'll like'."
During interaction	G3	**Time services based on context.** Time when to act or interrupt based on the user's current task and environment.	[Navigation, Product #1] "In my experience using the app, it seems to provide timely route guidance. Because the map updates regularly with your actual location, the guidance is timely."
	G4	**Show contextually relevant information.** Display information relevant to the user's current task and environment.	[Web Search, Product #2] "Searching a movie title returns show times in near my location for today's date"
	G5	**Match relevant social norms.** Ensure the experience is delivered in a way that users would expect, given their social and cultural context.	[Voice Assistants, Product #1] "[The assistant] uses a semi-formal voice to talk to you - spells out "okay" and asks further questions."
	G6	**Mitigate social biases.** Ensure the AI system's language and behaviors do not reinforce undesirable and unfair stereotypes and biases.	[Autocomplete, Product #2] "The autocomplete feature clearly suggests both genders [him, her] without any bias while suggesting the text to complete."
When wrong	G7	**Support efficient invocation.** Make it easy to invoke or request the AI system's services when needed.	[Voice Assistants, Product #1] "I can say [wake command] to initiate."
	G8	**Support efficient dismissal.** Make it easy to dismiss or ignore undesired AI system services.	[E-commerce, Product #2] "Feature is unobtrusive, below the fold, and easy to scroll past...Easy to ignore."
	G9	**Support efficient correction.** Make it easy to edit, refine, or recover when the AI system is wrong.	[Voice Assistants, Product #2] "Once my request for a reminder was processed I saw the ability to edit my reminder in the UI that was displayed. Small text underneath stated 'Tap to Edit' with a chevron indicating something would happen if I selected this text."
	G10	**Scope services when in doubt.** Engage in disambiguation or gracefully degrade the AI system's services when uncertain about a user's goals.	[Autocomplete, Product #1] "It usually provides 3-4 suggestions instead of directly auto completing it for you"
	G11	**Make clear why the system did what it did.** Enable the user to access an explanation of why the AI system behaved as it did.	[Navigation, Product #2] "The route chosen by the app was made based on the Fastest Route, which is shown in the subtext."
Over time	G12	**Remember recent interactions.** Maintain short term memory and allow the user to make efficient references to that memory.	[Web Search, Product #1] "[The search engine] remembers the context of certain queries, with certain phrasing, so that it can continue the thread of the search (e.g., 'who is he married to' after a search that surfaces Benjamin Bratt)"
	G13	**Learn from user behavior.** Personalize the user's experience by learning from their actions over time.	[Music Recommenders, Product #2] "I think this is applied because every action to add a song to the list triggers new recommendations."
	G14	**Update and adapt cautiously.** Limit disruptive changes when updating and adapting the AI system's behaviors.	[Music Recommenders, Product #2] "Once we select a song they update the immediate song list below but keeps the above one constant."
	G15	**Encourage granular feedback.** Enable the user to provide feedback indicating their preferences during regular interaction with the AI system.	[Email, Product #1] "The user can directly mark something as important, when the AI hadn't marked it as that previously."
	G16	**Convey the consequences of user actions.** Immediately update or convey how user actions will impact future behaviors of the AI system.	[Social Networks, Product #2] "[The product] communicates that hiding an Ad will adjust the relevance of future ads."
	G17	**Provide global controls.** Allow the user to globally customize what the AI system monitors and how it behaves.	[Photo Organizers, Product #1] "[The product] allows users to turn on your location history so the AI can group photos by where you have been."
	G18	**Notify users about changes.** Inform the user when the AI system adds or updates its capabilities.	[Navigation, Product #2] "[The product] does provide small in-app teaching callouts for important new features. New features that require my explicit attention are pop-ups."

This suggests that when learners perceive teachers (in distant modality) as present for learning support actions, they are more likely to continue learning. Therefore, the perceived presence of teaching support is crucial for users and warrants further study in AI applications.

Amershi & al. (2019) conducted an analysis of research and proposed a set of guidelines for designing Human-AI interactions (Table 1Table 2). This list of guidelines suggests general principles to adhere to when constructing AI interfaces, aiming to improve the usability and usefulness of the system and interface, as recently affirmed by the study conducted by Li & al. (2023).

However, as noted by other researchers, there can be as many AI interfaces as there are AIs and their intended uses. These guidelines should be approached by considering the specific needs of both the AI and the users interacting with it (Carvalho & al., 2022). The challenge of overly generalized principles is well recognized, and there are specific interaction guidelines tailored for VLEs, such as Mayer's guidelines mentioned previously.

4 CHALLENGES & PERSPECTIVES

4.1 IMPLEMENTATION NEEDS

The curriculum of the learning path (including learning goals, content, and assessment) is crucial when designing an AI learning environment (Kim & al., 2021). Particularly, in the acquisition of specific knowledge, the learning path should facilitate high-level cognitive processes, such as problem-solving and creativity, to support and enhance learning (Ouyang, 2021; Kafai, 2014).

Continuing with the curriculum, institutional support plays a vital role in the development of AI for Education (AIED), ensuring the provision of a learning environment with adequate digital infrastructure (Wang, 2021) and allocating time for the appropriate methodology of AI implementation within the institution (Zawacki-Richter, 2019).

Furthermore, instructors themselves need support in their understanding of AI, introducing them to AI literacy. Instructors who are not familiar with AI concepts and operations may exhibit reluctance and lower acceptance of AI technologies (Lin C.-C. L.-Z.-I., 2017).

4.2 DATA PRIVACY

The potential of AI in education (AIED) hinges largely on personalized learning (Chen X. Z., 2021). However, to train an AI model effectively, extensive training data, often including personal information, is required. Therefore, safeguarding this data is imperative, whether it is for internal or external use.

It is crucial that teachers do not have unrestricted access to all learner data. Additionally, it is essential to recognize that algorithms themselves may be influenced by the limitations and cognitive biases of their creators. For instance, an algorithm developed based on simplifications or neuro-myths could have adverse effects on learners.

Care must be taken to avoid promoting the use of AI to create systems that categorize and prescribe "learning styles," as this approach may constrain learning within predefined boxes.

Neuro-myths, such as those surrounding brain gym exercises or learning profiles, persist despite evidence to the contrary. Acknowledging that learning is a multifaceted process that defies simplistic categorizations should be a priority to prevent the misuse of AI in education, thereby avoiding the propagation of techniques ill-suited to genuine learning.

4.3 CONCEPTUAL RESEARCH VS EXPERIMENTATION

At the conclusion of this document, it is imperative to address the prevailing dearth of research on the intersection of AI and education as of 2023. The bulk of existing studies tend to involve a limited number of participants or revolve around meta-research and conceptual design, often lacking direct experimentation (Dai & Ke, 2022).

Direct experimentation poses a challenge in the current landscape, primarily due to the complexity involved in coding genuine AI programs, particularly within the realm of education. However, the necessity for experimentation involving actual learners and real AI systems is steadily growing in significance. This shift underscores the pressing need for more empirical research and practical applications to advance our understanding and utilization of AI in educational settings.

5 Conclusion

This deliverable focuses on the theoretical basis and practical research results accumulated on the topic of AI uses in education, from the cognitive mechanisms linked to learning to the field studies using AI-based systems in the classroom.

The fundamental strength of an AI-based simulation as underlined by this literature review is the autonomy provided to the learner. This grants the learner the opportunity to cultivate intrinsic motivation, one of the main scaffolds of self-learning. It also offers the learner a safe learning space, without judgemental gaze or pressure, akin to an educational sandbox. Lastly, coupled with a tailored or adaptable difficulty level and a feedback system, this type of learning resource ensures that the learning will occur in the optimum zone that neither discourages nor under-stimulates the learners, allowing for an autonomous management of their cognitive load.

In addition, the amount of context – domain-specific or general knowledge – which can be given to such AIs makes it both highly adaptable and generalist enough to manage most interactions with learners. It allows for a variety of highly specific scenarios while enabling recovery of simulated learning situations that stray off course. This is particularly crucial in the field of application chosen for this project: soft skills in VET for the tourism industry.

The greatest added value of education in this era of work automation is indeed the teaching of soft skills. The learners will be put in situations that imply complex emotions, rich backgrounds, legal requirements, ethical problems, miscommunication. Simulated agents should display complex human behaviour while the simulation engine should guide the learners and monitor the whole training exercise.

The other side of the coin of using generative AI such as Large Language Models (LLMs) is that reliability may be limited, due to the randomness introduced by the generative aspect of LLMs. Furthermore, AI-based simulations feature two other large categories of limitations: intellectual property issues linked to training on vast datasets that are sometimes opaque, and accountability issues linked to the mostly “black box" functioning of LLMs. These aspects will be explored in deliverable 2.3 of this project.

As studies on AI-based learning using generative AI are still scarce, the outcomes mentioned are only theoretically predicted, verified in adjacent fields of application, or observed in a handful of practical cases. There is a need for additional research to fully confirm those effects, which this project intends on contributing to. The best practices and guidelines in design and development cited in this document will be used to this end.

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