PERSONALIZED LEARNING IN THE ERA OF DIGITAL LEARNING AND ARTIFICIAL INTELLIGENCE: FUTURISTIC PERSPECTIVES AND CHALLENGES
APPRENDIMENTO PERSONALIZZATO NELL'ERA DELL'APPRENDIMENTO DIGITALE E DELL'INTELLIGENZA ARTIFICIALE: PROSPETTIVE E SFIDE FUTURISTICHE

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ABSTRACT

This is a narrative review about personalized learning and how digital learning impacts students and teachers' roles and lifelong learning. AI is changing learning designs, providing learner-centred approaches, and less burden for educators. Yet, digital managerial and ethical challenges related to artificial consciousness and machine autonomy are also rising. Urgent research and ethical considerations will guide the use of these powerful tools.

Questa è una revisione narrativa sul *personalized learning* e su come la digitalizzazione influisce sui ruoli di studenti e insegnanti e sul *lifelong learning*. L'intelligenza artificiale sta cambiando la struttura educativa, con approcci incentrati sullo studente e meno pressione sugli educatori. Tuttavia, stanno emergendo sfide etiche e organizzative nei campi di coscienza artificiale e *machine autonomy*. Sono richiesti studi scientifici e etici per guidare l'uso di questi potenti strumenti.

The study is the result of a joint collaboration between the authors:

- *Leila Ali wrote the Introduction and the first paragraph of the discussion "Basic definitions: learning and digital learning"*
- *Leila Ali and Clorinda Sorrentino wrote the second and third paragraphs of the discussion " The role of the teacher in digital learning and AI" and "Learning designs; the past and the Future"*
- *Lucia Martiniello wrote the paragraphs Limitations and suggestions for future research and the conclusions.*

Introduction

Multiple theoretical frameworks defined personalized learning (PL) as a learner-centered-approach(Walkington & Bernacki, 2020). All theories highlight the role of environment in the pathway of PL to reach a state of mastery of learning. This interaction of the learner with the environment is reciprocal. The learner participates both in co-designing the instructional approach and obtaining his learning needs through ownership of learning. This interaction between individualization and differentiation optimizes learning by combining personal interests and motivation to agency and choice(Walkington & Bernacki, 2020). PL has many degrees of depth from surface (attention based), to medium (interest based) to deep (involvement based), and different grain sizes from targeting populations, to groups of students to individuals. Technology plays a major role in modulating the environment of PL and offers flexible and innovative tools for students and teachers. Artificial Intelligence (AI) moreover, changed the learning paradigm from human centered to human and machine centered. Through conversational AI platforms like chatGPT learning is no longer limited to humans but extends to the machine. This study aims to bridge the gap between cognitive neuroscience and pedagogy by defining the intricate relationship between personalized learning, digital education and AI.

Discussion:

A litterature review was performed through a theoretical approach to define learning, digital learning and personalized learning from a philosophical and neuroscientific point of view, and to identify the impact of digitization on the

teacher's role and learning designs. The following research questions will be analyzed:

1. What is the learner's role and the ultimate learning purpose in the digital era?
2. What is the role of the teacher in digital education and AI?

3. What are the past and future learning designs in education and how can they achieve PL?

At the end a representative diagram of the different actors and components of PL in the digital era will be suggested.

1. Basic definitions: Learning and digital learning

A. The learner and the ultimate goal of learning:

Philosophy of learning and PL: Epistemology of learning is a philosophical branch that describes the nature of knowledge as a state that occurs between belief(subjectivism) and truth(objectivism) (Hamati-Ataya, 2014). The different theories of learning align at different degrees with these states. Philosophical learning theories are subdivided into: 1. Instrumental learning theories including: Behaviourism that is teacher centred and stipulates that people learn passively through repetitive environmental stimuli (Lockey et al., 2020), cognitivism (cognitive information processing theory, meaningful learning and schema theory, and experiential theories (Mukhalalati & Taylor, 2019)) that are learner centred and consider that the brain conceptualizes and processes information as a whole (Lockey et al., 2020). 2. Interactional social theories that focus on knowledge as an overlap between truth and belief and include Bruner's interactional theory, Vygotsky's interactional theory, learning-by-doing situated cognition theory, communities of practice (Mukhalalati & Taylor, 2019), and finally connectivism that emerged in the digital era and that highlights the importance of human interaction in learning and developing combinational creativity (Siemens, 2018). 3. Constructivism that has rather a humanistic approach and focuses on experience-based-learning (Lockey et al., 2020). 4. Other adult learning theories include motivational models, reflective models, humanistic self-directed learning and transformative learning and highlight that action results from metacognition based on experience (Mukhalalati & Taylor, 2019).

behaviourism and cognitivist theories tend towards objectivism, Interactional theories overlap between truth and belief, and adult learning theories are more based on belief (figure1).

EPISTIMOLOGY OF LEARNING

Truth: Objectivism   Knowledge   Belief: Subjectivism

| Behaviorism 1900s | Cognitivist theories | Interactional social theories | Other adult learning theories |

- Andragogy 1830s
- Cognitive information processing 1950s
- Multiple representation based learning 1960s
- Schema theory 1970s

- Vygotsky's interactional theory 1970s
- Bruner's interactional theory 1980s
- Communities of practice 1991
- Situated cognition 2000s
- Simens connectivism theory 2004

- Self-directed learning 1970s
- Transformational learning 1970s
- Reflective models 1987s
- Motivational models 1992-2000s
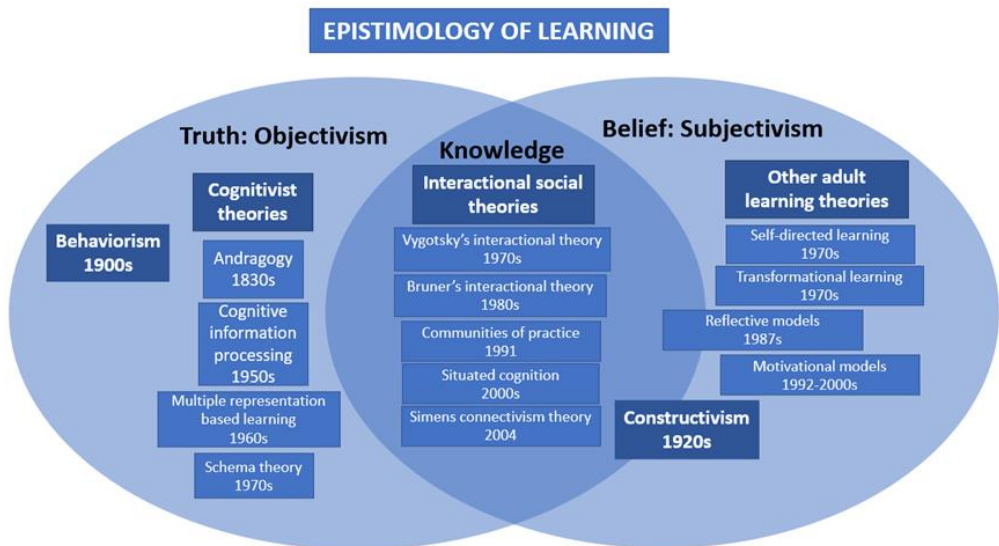
Constructivism 1920s

Figure 1 Epistemology of learning

Schommer stated 4 personal dimensions that interfere with PL that are: control, speed of learning, organization of knowledge, and certainty of knowledge. Theories of PL include mastery learning, differentiation, self-determination theory, interest theory, strengths-based learning, funds of knowledge, connectivism, distributed leadership, situated cognition, and metacognitive thinking (Walkington & Bernacki, 2020). Figure 2 summarizes how PL theories are designed based on their focus on the learner or his environment.
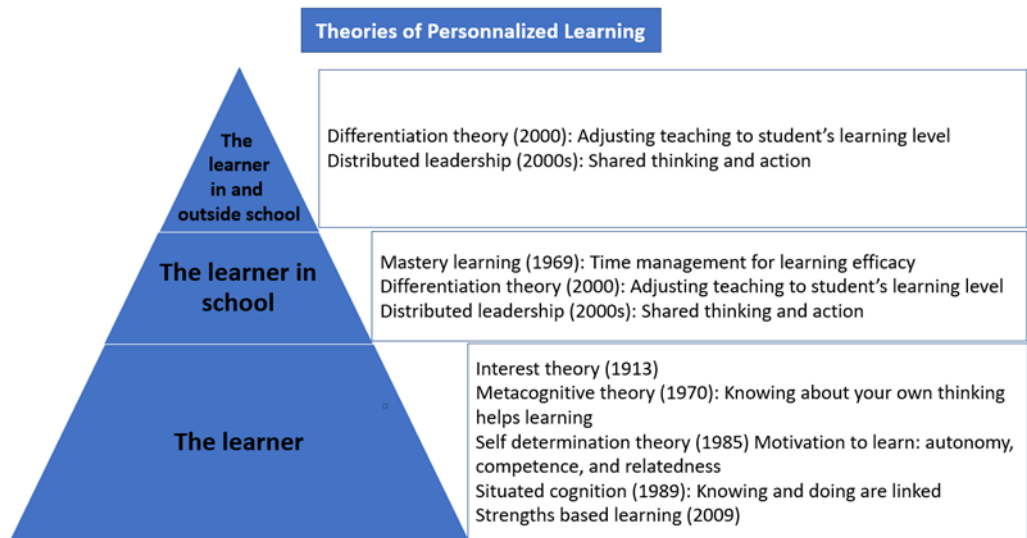
Figure 2 Theories of PL based on their focus on the student and his environment

B. Digital learning

Virtual learning (VL)

VL was established for the first time in 1999 (Hubackova, 2015). It wasn't however until the COVID pandemic, that it has become the principal educational resource for education in academic institutions worldwide (Jouf University & Humayun, 2020). There are 8 principal categories of eLearning platforms; Digital learning management systems (DLMS) based on computer science system that allows to plan, implement and access learning like moodle, canvas, schoology, edmodo, and google classroom, Massive Open Online Course Platforms (MOOCP) based on open course, participatory, online, and lifelong network learning, Self-directed learning content (SDLC) based on personalized learning, motivation, and self-management, Mobile reading applications (MRA) like cell-Ed, Funzi, Kai-OS, Collaboration platforms for live-video communication (CPLVC) like zoom, microsoft teams, and hangouts, Tools for teachers to create digital learning content(TCDLC) like Edmodo, socrative, tedEd, project, thinglink, animoto, and kahoot, External repositories of

distance learning solutions (ERDLS), Systems for basic mobile phones (SBM) and Systems with strong offline functionality (SSOF)(Jouf University & Humayun, 2020).

AIEd

The concept of AI was first introduced in research between the 1940s and 1950s with the birth of computer science. It includes processing systems that can learn and predict information by managing 'big data'. The use of AI in education is mainly based on machine learning. The branch of machine learning includes data analytics, reinforcement learning and deep learning through neural networks. Modern AI focuses creating autonomous machines that do not require human control for learning and contextual adaptation. The first publication about 'AI in education' (AIEd) date to 1989 in the International Journal of Artificial Intelligence in Education. AIEd is basically framed by pedagogy and conceptualized through cognitive science (Williamson & Eynon, 2020). Intelligent tutoring systems (ITS) are innovative AI tools characterized by a high adaptability to the learner's needs and learning styles, and precision in terms of educational, psychological and social requirements (Schiff, 2021). Moreover, ITS enhance students' sustained attention, detect their emotions, and teach them physical motor skills (Schiff, 2021). Some powerful ITS have social emotional capacities, like embodied virtual robots and conversational tools based on machine learning like ChatGPT. In 2022, after its release by OpenAI, ChatGPT could provide diverse information from a pre-existing database in many languages (van Dis et al., 2023). It is developed through an imitation of cognitive processes involved in perception and cause-effect reasoning known as "causal cognition". This tool is revolutionizing access to information, and societal roles on the terms that machine may replace many human jobs and functions (van Dis et al., 2023).

C. Neuroscience of learning and PL

The basic structure of the brain is hierarchically organized into 3 layers in depth from the inside to the outside: the brainstem responsible of basic life support, the limbic system involved in core valuation that analyses the external and internal environments to control drive and survival instincts through emotions like desire (ventral striatum) and fear(amygdala), and the cortex involved in higher functions like cognition and consciousness. These different layers interact with each other in order to provide optimal survival and wellbeing. The cortex and limbic system participate in learning processes. Cognitive functions involved in learning are: short term or working memory (WM), long-term memories including declarative (DM)

and procedural memory (PM), and executive functions (EF). Other cognitive functions like language, and social cognition also interfere with learning, intelligence and creativity at a secondary level.

Memory: Memories are dichotomized into short-term memory and long-term memory. Short term memory includes immediate memory and working memory (WM). While long term memories include episodic/ declarative (DM) and implicit/procedural (PM). WM is responsible of short-term storage and manipulation of information. It requires a central executive (prefrontal cortex: PFC), an attention controller (anterior cingulate cortex: ACC), an episodic buffer (parietal lobe), a visuospatial sketchpad (occipital lobe), and a phonological loop (Broca and Wernicke language areas) (Chai et al., 2018). Working memory is the first cognitive interface used to integrate new information, and is limited in terms of the amount and duration of information storage. The neural connections obtained through working memory are weak. It serves for temporary manipulation of new information and we can use it in many cognitive tasks, like calculations, learning new names, keeping instructions in mind during practice. The more knowledge people acquire the better their working memory performance is (Chai et al., 2018). In fact, WM organizes learning information into mental models or schemata, in order to transfer them to long-term memory. This process induces an intrinsic cognitive load (ICL). Three factors participate in moderating the ICL: 1. The number of elements that need to be processed simultaneously, 2. The amount of prior knowledge in a specific domain, and 3. The degree necessary to build new mental models (Schneider et al., 2022). Studies showed individual differences in verbal working memory performance between individuals using Classical classroom learning (CCL), virtual learning (VL), and ITS (Fellman et al., 2020; Tetzlaff et al., 2021), an improvement in WM span after using PL (Tsianos et al., 2010), and a better WM after reducing cognitive load with ITS (Courtemanche et al., 2008). With declarative memory, consolidation is a conscious process that happens through hippocampal engram formation. Engrams are the biological synaptic correspondents of memory. The CA1 hippocampal region has two group of cells; place cells responsible respectively of stocking spatial memories (Miry et al., 2021), and time cells for verbal memories (Clark & Martin, 2018). Another group of cells called index cells may interfere with contextualizing memories, a process that helps in memory consolidation and retrieval (Miry et al., 2021). Practices that reinforce and help memory retrieval are still controversial (Miry et al., 2021), yet synaptic activation and neuroplasticity are reported to play an important role in memory consolidation and retrieval (Josselyn & Tonegawa, 2020). Empirical practices in learning and education that are used to stimulate brain activity and memorization

include: retrieval practice, rereading, highlighting information, and creating concept maps (Karpicke & Blunt, 2011; Moreira et al., 2019). We hypothesize that the observed efficacy of retrieval practice in memorization may be due to reinforcement cues and contextualization of information of index cells, and reinforcement of synaptic activity and neuroplasticity in engram cells. Other studies highlighted the importance of sleep-in memory consolidation and this fact is due to the fact that engram reactivation occur during sleep (Ghandour & Inokuchi, 2022). With procedural memory, memorization is an unconscious process that happens within the basal ganglia and cortico-striatal loops (Knowlton & Moody, 2008). There are four major cortico-striatal loops: 1. The motor loop that links the motor and premotor cortex to the putamen, 2. The executive loop that links the prefrontal cortex (lateral and ventral) to the anterior caudate nucleus, 3. The visual loop that links the inferior temporal lobe to the posterior caudate, 4. And the motivational loop that links the ventromedial prefrontal cortex to the ventral striatum (Seger & Spiering, 2011). This explains why procedural memory interferes with motor control, cognitive coordination and emotional function (Seger & Spiering, 2011). Procedural memory is stimulated by dopamine reward circuitry and can bias our behaviour and conscious thinking (Uddén et al., 2010). In fact, decision making depends on three major actors: the dorsolateral PFC responsible of cognitive context (facts/reasons), the amygdala and ventral striatum responsible of core valuation (drives) and the dorsomedial PFC responsible of emotional context (linkages)(Kennerley & Walton, 2011).

Recent studies showed individual dynamic differences in DM and PM in language learning and the importance of exposure and proficiency in the interconnection between DM and PM in CCL (Morgan-Short et al., 2014). VL increased students' motivation to learn (Noor et al., 2022), however, they could not identify if learning behaviour was linked to motivation. Other studies showed VL ineffectiveness in skills learning (Hong et al., 2021) and a negative impact of VL on DM due to emotional distraction (Khakim & Kusrohmaniah, 2022). AIEd tools seemed to improve WM and DM in personalized language learning (Ruiz et al, 2021). Studies have shown that procedural knowledge and interventional activities improve PM in CCL (Saks et al., 2021). Further research should be performed to understand the impact of digital learning on PM.

Executive functions (EF) are conceptualized by Miyake into three components: working memory, inhibitory control and cognitive flexibility (Shokrkon & Nicoladis, 2022). These components together contribute to higher EF like reasoning, problem solving and planning. EF are mediated by the prefrontal cortex and their

development is interconnected with linguistic skills and memory (Gunzenhauser & Nückles, 2021; Shokrkon & Nicoladis, 2022). In fact, the more acquired knowledge people have, the better their EF performance is (Gamino et al., 2022). Studies showed that digital use may affect inhibition decision making, while video games engaging material can improve working memory (Warsaw et al., 2021). However, many of these studies had methodological biases. Other papers stated that some AI tools based on user-machine interfaces, robotics, and virtual reality can improve EF still further research should be performed while considering all the variables that might interfere with the human-AI interaction (Robledo-Castro et al., 2023).

Research in the field of cognitive neuroscience identified individual differences in learning (Wong et al., 2017). These may interest many cognitive domains and their particular dominant neurotransmitter systems. There are genetic and non-genetic biomarkers of PL. Genetic biomarkers include cluster genes of the glutamate system for episodic memory, dopaminergic receptors D2 of striatal system for procedural memory, and dopamine D1 receptor genes for working memory. Non genetic biomarkers include psychometric intelligence, executive function and working memory (Wong et al., 2017). These biomarkers play a major role in predicting the individual outcome of learning. Figure 3 summarizes the brain function involved cognition and learning.
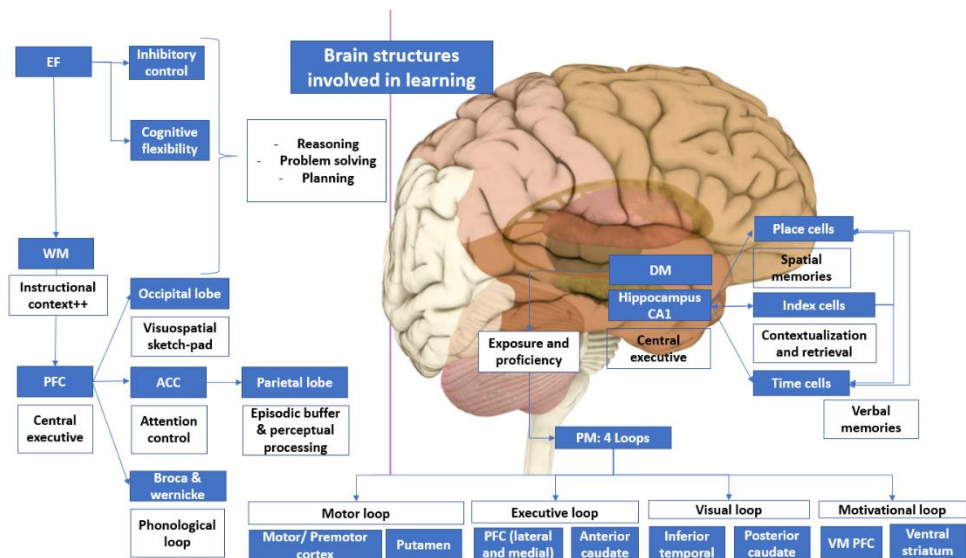

Figure 3 Brain structures involved in learning

Other cognitive functions like language, social cognition, and metacognition interfere with learning on a more complex level. Linguistic skills are important for

interaction and communication, social cognitive skills are associated with higher intelligence and metacognitive skills are linked to higher resilience and inner awareness. Studies have shown that using digital tools can improve foreign language learning (Bećirović et al., 2021; Carrier et al, 2017), not only that conversational AI tools and technologies based on interaction theory have a powerful potential in implementing methods for PL, content creation, reducing work load for teachers and students, and also moving on with creativity from its traditional aspect to a new creating fast specific facilitated creative content (Ji et al., 2023). The theories of social processes involved in digital environments defined the human-computer interaction as a social event that depends on many social cues within media environments (even in the absence of actual humans) (Schneider et al., 2022). Some of these theories include media equation theory, computers-as-social-actors paradigm, para-social interaction, social presence, and the cognitive and affective social theory of learning in digital environments (Schneider et al., 2022). Empirical studies identified individual differences within social schemes of this human-machine interaction (Schneider et al., 2022). This social interaction with digital environment uses sensory memory, WM, and long-term memory to stimulate social cognitive processes and metacognition (Williams et al., 2022).

Cognitive neuroscience of learning highlights the sensitivity of the brain-environment interaction for intellectual growth and the importance of implementing brain-healthy strategies of education to reach a state of mastery of learning. The use of technologies should consider the role of environment, the cognitive strategies used for learning, and the impact of procedural memory solicitation on motivation, habits and practical skills acquisition. AIEd is a powerful tool for the future of PL; it offers what CCL and VL failed to provide, in terms of cognitive demands of learners, and immediate and free access to information. Yet, drawbacks of technology use on learning performance and outcomes need to be considered and evaluated through experimental research. Some of these concerns include the potential negative impact of digital tools on working memory, language learning and memorization, and the possible impact of chatGPT on critical thinking, and human to human social emotional cognitive skills. Technical surveillance of AIEd is also challenging in many ways. Academia pointed some incidents of students using ChatGPT to provide answers in their place at exams. Such concerns raised questions on how will we differentiate whether AI provided the answer or the student. As a response, human centered AI detection tools like detectGPT, and GPTzero have been developed to differentiate machine writing from human writing

(Mitchell et al., 2023; Stokel-Walker & Van Noorden, 2023). Many ethical concerns are shared on whether AI can alter common sense and the perception of diversity due to "common thinking schemes". Other concerns are related to the accuracy and up-to-datedness of information in data banks used by AI platforms. Scientific communities using chatGPT reported also that it is "fluent but not factual", and that it has "little specificity and safety". They suggested the importance of enforcing honest use of chatGPT in scientific papers through laws on discrimination, bias and transparency (van Dis et al., 2023).

2. The role of the teacher in digital learning and AI

The role of the teacher in VL switched from being a "source" of information to simply "stimulating", "guiding" and "managing" the learning process and access to information. Teachers rely more on students' autonomy and should be more aware of learners individual differences(Isman et al., 2004). Teachers in VL need also to acquire high communication skills, multiple pedagogy learning tools, and technology skills(Isman et al., 2004). AIEd and ITS are capable of replacing the teacher in terms of accessibility and accuracy of information, personalized students' needs, and even emotional interaction and motivation(Schiff, 2021). There are challenges regarding the use of AI tools in the classroom and opinions are merging towards the future role of teacher in classroom orchestration where human teachers manage not only the learning activity but also human-computer interaction(Ji et al., 2023). Practical guidelines and AI based classroom orchestration tools were developed to help teacher manage AI based learning(Ji et al., 2023). Ethical and social repercussions need to be considered with this fast and tremendous development of technology. Many questions remain unanswered related to the huge societal role-shifts of replacing teachers with AI devices, and humans with AI-human assistants.

3. Learning designs; the past and the future

Differences and overlap between CCL and VL

CCL was initially based on two relationships: a vertical relationship between the educator and the learner where the educator is both a source and a manager of information. And a horizontal relationship between learners where exchange of information is more complex and dynamic. Another important aspect of CCL is the

shared environment: the classroom (Suleri & Suleri, 2019). The term CCL dynamics emerged after as an important factor of learning efficacy (Doveston et al, 2006). The dynamic of the classroom focuses on involving students in the design and evaluation of learning, switch the roles during the learning process from teacher centered to students centered and provide flexible study frames that fulfill students interests and needs. PL in classical classroom has been particularly adopted by the USA educational policies since 1779 (Dockterman, 2018), by switching the uniform instructional model to address the different cognitive, affective, and behavioral needs of each student (Dockterman, 2018). PL pedagogy was the trigger motivating the use of technology in the classroom, and the evolution of education from classical, to blended to digital (Suleri & Suleri, 2019). Blended learning (BL) is a mode of learning that combines VL and CCL (Suleri & Suleri, 2019), and is a good representation of the overlap between them. It combines both the comfort of VL, better PL tools, and also the social, physical and environmental interactions provided by CCL. Computers provided adaptive learning tools that help accommodate to students variability (Dockterman, 2018). Inclusion of adaptive social cues helped social interaction in digital learning environments and stimulated students social engagement with digital learning (Schneider et al., 2022).

Differences and overlap between VL and AIEd

VL and AIEd are similar in the way that they use digital tools, try to change the teacher's role, and try to achieve massive and low-cost access to science. However, they are different in many aspects; distance learning lacks intelligent socio-emotional features, and has less individualization and differentiation compared to AIEd. Moreover, AIEd is proposing innovative tutoring skills that may replace traditional human teachers (Schiff, 2021). As a potential tool in PL, chatGPT offers the user, free, instant and easy access to information, in many ways that the teacher-learner classical tools may fail. For example, a learner might ask ChatGPT to explain a certain phenomenon. According to the answer provided, the learner may not understand some terms so he/she can ask about their meaning and get an instant response. In this way, understanding and optimal learning are very likely to occur because ChatGPT responds precisely to the student's needs. This might not happen with the teacher-student learning pathway either via VL or CCL due to lack of information and knowledge about each students' personal interests and limits. Digitization can impact the evolution of consciousness from "collective" to "individual" to "artificial". In fact, CCL design offered students in the past a common environment, similar information resources and similar evaluation of knowledge.

VL provided more personalization in terms of choice of the place, time and rhythm of learning, and multiplied the information resources. Yet, it was still limited in terms of personalization and instant access to knowledge. AIEd however, is proposing a new design where information is illimited and learning is not limited to the human but also extends to the machine. Integrating AI in education will lead to major societal shifts regarding the teacher-learner relationship. The concept of "classroom" from a limited physical or virtual learning environments, to a human-machine individualized lifelong learning interface. Nevertheless, AIEd is still limited when it comes to transferring relevant knowledge from one domain to another, phenomenal sensations of feeling and desire, and intentional pull that drives teleological behavior (Bishop, 2021). This humanity gap with AI highlights the role of the human interaction with the machine and the importance of the data pool reliability to deliver accurate information. The problematic with new technologies is their controversial aspect on whether or not they may substitute human intelligence in the field of education, and if they might negatively impact human creativity and cognitive functions on the long term.

Design differences in CCL and VL/AIEd

VL conceptualization relies on four major actors: students, teachers, design groups and directors. Three types of interactions are observed in VL: 1. The interaction between the learner and the content, 2. The interaction between the learner and instructor, and 3. The interaction between the learners (Isman et al., 2004). Using textbooks and lectures are common between CCL and VL. And both of them lack the AIEd 'intelligent' feature. AIEd is characterized by its personalized and immediate feedback compared to CCL and VL (Schiff, 2021). AIEd relies on four domains: expert domain, learner domain, pedagogical domain, and a student-learner interface (Schiff, 2021). More than distance learning it provides a more personalized approach and tutor-learner relation.

To summarize we propose in figure 3 a landscape of PL in the digital era, and the different related designs of learning in CCL, VL and AIEd.
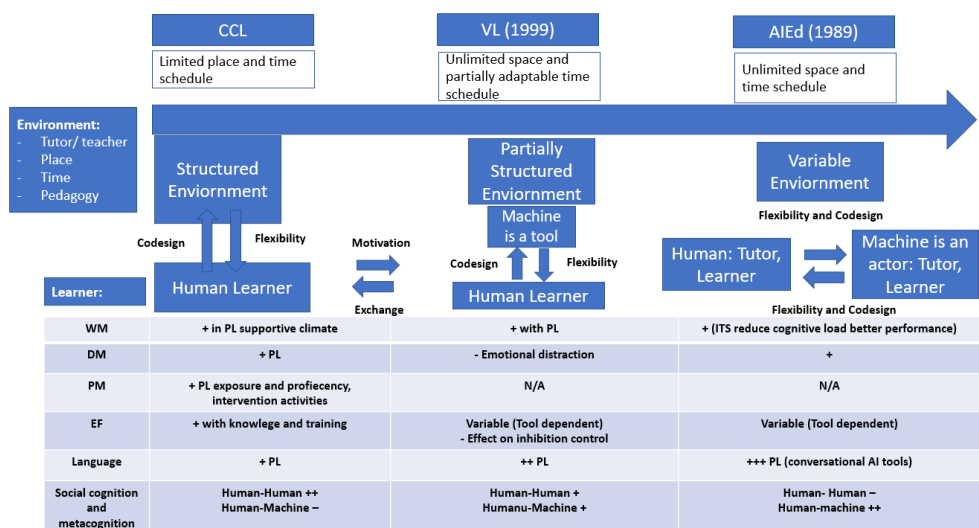
CCL

Limited place and time schedule

VL (1999)

Unlimited space and partially adaptable time schedule

AIEd (1989)

Unlimited space and time schedule

Environment:
- Tutor/ teacher
- Place
- Time
- Pedagogy

Structured Enviornment

Partially Structured Enviornment

Variable Enviornment

Machine is a tool

Flexibility and Codesign

Codesign — Flexibility

Motivation

Codesign — Flexibility

Human: Tutor, Learner

Machine is an actor: Tutor, Learner

Learner:

Human Learner

Human Learner

Flexibility and Codesign

Exchange

	CCL	VL	AIEd
WM	+ in PL supportive climate	+ with PL	+ (ITS reduce cognitive load better performance)
DM	+ PL	- Emotional distraction	+
PM	+ PL exposure and proficency, intervention activities	N/A	N/A
EF	+ with knowlege and training	Variable (Tool dependent) - Effect on inhibition control	Variable (Tool dependent)
Language	+ PL	++ PL	+++ PL (conversational AI tools)
Social cognition and metacognition	Human-Human ++ Human-Machine −	Human-Human + Humanu-Machine +	Human- Human − Human-machine ++

Figure 4 The pathway of PL in the digital era: Evolution of PL design

Limitations and suggestions for future research

The current study presents several limitations. First, only English written search databases were included. Future studies should consider widening the scope of review to papers written in other languages. Also, this study reported the pedagogic and neuroscientific representations of learning in the digital era. Future research can focus on experimental works targeting cognition and digital learning and the impact of learning designs on cognition and mastery of learning. It wasn't until recently that conversational AI tools have become available worldwide. Only few lab-conducted research papers studied the role of AIEd in the classroom. Many questions are still unanswered about the impact of AIEd on cognition and how to design and regulate this human-machine interaction for learning purposes. In addition, the role of teachers in the era of AIEd should be clarified further through appropriate policies based on theoretical and experimental research models.

Conclusions

The first section of this review summarizes definitions of learning and PL from a philosophical and neuroscientific point of view. And identifies the main hypotheses used in learning and PL and their related objectivism, knowledge based and subjectivism aspects. PL theories diverge from learner centred to classroom and

broader environment approaches. In cognitive neuroscience the functions involved in learning are memory (WM, DM and PM), EF and other functions like language, metacognition and social cognition.

The second section of this review outlines the principal digital tools used in VL and AIEd. It also discusses how the teacher's role evolved from being the source and manager, to simply orchestrating information and how AIEd have potential power to replace the teacher in the future. Finally, the impact of digitization on transforming the scheme of learning designs was discussed. These designs are moving forward with learning from its collective approach to a more personalized one. AIEd does not only consider the "human" and human-to-human interaction as targets of learning, but also expands to the machine. The machine in these designs can also be a learner and the human-machine interaction can be considered as a social event. The dramatically fast evolution of technology made access to information instant and global. Many new concepts emerged from this: like lifelong learning, freedom of learning, microlearning, personalized learning and AIEd. Digitization is breaking the physical environmental barriers that are found in democratized learning, and classical classrooms, and the temporal ones like defining a certain age to learn, learning in definite hours. There are many controversies regarding the challenges related to artificial consciousness, impact on cognition and creativity, and the actual social structure and order. The impact of digital advances on the future of PL is huge and also inevitable. PL is a potential powerful tool that can bridge the gap between education and employability, by providing adapted curricula to the scheme of the job market and learners personal interests. It also can help employees adapt to the evolution of technology in the workplace through appropriate lifelong learning programs adapted to the workplace. It is however important to implement urgent experimental research and manage digital technology to serve the common good and advance with scientific research while maintaining reasonable ethics that consider the social and economic structures.

Conflicts of interest none.

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