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[1] The French National Research Agency (ANR) is a public administrative institution under the authority of the French Ministry of Higher Education, Research and Innovation. The agency funds project-based research carried out by public operators cooperating with each other or with private companies. https://anr.fr/en/anrs-role-in-research/about-us/missions/

[2] PIA 3 **Et-Lios** (https://et-lios.s-mart.fr) - Open LIcence-level Technological Education for a competitive and sustainable induStry of the future. Project for the hybridisation of higher education courses 2020

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CHAPTER 1: INTRODUCTION

1.1 INTRODUCTION

The investigation of adaptive learning environment has gradually shifted from a techno-centric instructional approach, which focuses mainly on transmitting knowledge from an expert or artificially intelligent system to the learner, to a human-centric approach, in which knowledge is constructed by a wide range of learners and actors who are actively involved in the learning experience and are engaged in collaborative work with machine, experts and their peers.

Adaptive learning environments are expected to support better human-centric personalized solutions of learning that enable more self-paced, self-directed, self-regulated, self-efficacy learning. Self-adaptive learning can be generally defined as the human being involved in the adaptation to the complicated world, ubiquitous learning environments, and hybrid or adaptive learning systems to obtain learning resources; discover their own motivation and preferences; interact accordingly with the adaptive contents; collaborate socially with the others and to obtain support in acquiring required knowledge and competence; construct significant learning in the progress; and grow from their personal learning experience within contexts and across. However, there are several issues regarding the construction of a personalized adaptive deep learning ecosystem. In most systems, the sources and types of adaptation are often taken into account to an insufficient degree, in other words, the investigation and implementation of both issues of adaptivity and adaptability are not sufficient. Most adaptive learning environments only consider the sole type or single dimension of adaptation due to the lack of integration of innovation of trans-disciplinary knowledge, management of human resources, advancement of technology, and systemization of multiple systems and services in adaptive learning programs. The collection of learning data suffers from the issues of insufficiency, diversity, utility, validity, value, and these make learning analytics become even more difficult and less effective to generate the adaptive evaluation of intervention solutions in order to provide truly personalized and adaptive learning (Brusilovsky,2020). Furthermore, a large volume of resources may still overwhelm them during the process especially if they do not know preciously how, when, where, and what to learn better or effectively, and they face conflicts and risks if they don't develop resilience in learning. This may make them less aware in how to transfer knowledge appropriately into long-term and deeper memory, it may lead to less effective way in the acquisition of higher-order skills. Traditional adaptive e-learning environments tend to provide fixed and pre-set rules of adaptation in the same sequence to particular groups of users, which may be problematic for personalization, and lead to poor experience and performance. Adaptation is often put forward as a way of personalization of learning, customization of services, or tailoring a system to the user's requirements. Some learning systems (e.g., intelligent tutoring system, adaptive instructional system, emotional adaptive learning system, intelligent adaptive learning system, adaptive companion system, personalized adaptive learning system), often integrate different theoretical models to provide adaptive services, and to recommend relevant personalized instructional materials; they are an enhancement to the dominant, one-size-fits-all approach to the development of adaptive e-learning systems with the one-fits-one or all-fits-one size approach. An adaptive deep learning system may emphasize appropriate timely materials, recommend the content for a given learner, make the adaptive evaluation, construct the personalized learning sequences, navigate the learning paths.

Since this thesis presents research concerning hybrid flexible and personalized adaptation in an adaptive learning ecosystem in which learning resources can be customized and appropriately sequenced to meet the needs of individual learners, it takes the transdisciplinary approach that draws from the fields of education and computer science, including subjects of STEAM[3], psychology, learning, cognition, brain and neuro science. The specified research questions in this

[3] STEAM is an acronym for Science, Technology, Engineering, Art and Mathematics. https://fr.wikipedia.org/wiki/Steam

thesis are best answered by combining the theoretical concepts and empirical evidence of these two major disciplines.

In the field of education, several conceptual models draw from psychological theories (e.g., humanistic psychology, behaviorist, constructivism, developmental psychology, Gestalt [4] psychology, social learning theories); from cognitive theories (e.g., cognitive load, cognitive flexibility, cognitive semiotics), other contemporary learning theories (e.g., connectionism, connectivism, gamified learning, theories of multiple-intelligence and self-efficacy).

It is becoming critical for designing and implementing learning systems to identify why, when, where, how, and what human prefer to learn and can learn well. Thus, understanding of different interesting factors such as learning goals, personality traits, and learning preferences has been the key issue in developing personalization and adaptation in order to meet learners' requirements.

Amongst these variables, mastery of knowledge and learning experience are recognized as major factors in learning quality. In the computer science field, the investigation of personalized and adaptive deep learning systems remains a crucial issue for researchers. The development of adaptive methods, techniques, and tools represents an important concern in adaptive learning ecosystem. These techniques specify the ways that learning content and information are presented and sequenced to meet the needs of learners. The major focal points of the investigations related to the development of adaptive models and frameworks, which aim to facilitate the design and the implementation of adaptive learning environment. The comprehensive didactic framework, which is mainly constructed in Chapter 2 explains cognitive processes, knowledge acquisition, learning mechanisms, and intelligent adaptive learning features. Chapter 3 constructs adaptive learning conceptual reference framework, which incorporates the main components and techniques that are necessary to provide adaptation. The added models and mechanisms (e.g., meta-cognitive auxiliary

[4] https://www.usabilis.com/definition-theorie-de-gestalt/

model, intervention mechanisms, adaptive learning analytics and evaluation models) are proposed for the construction of deeper self-efficacy learning experience. The taxonomy of learning analytics in Chapter 4 classifies diverse adaptive indicators, techniques, methods, tools. These studies should provide common recognized and comparable references for identifying adaptive sources and relevant rationale for further enhancing multimodal learning analytics and development of feedback loops.

The following chapter introduces the motivation for this work and its relevant background. It also outlines the research problems that are identified. It then specifies the research objectives, questions, methodology, and highlights the contributions. The structure of this thesis, that constitute entire body of work is also presented.

1.2 BACKGROUND AND MOTIVATION

The provision of learning contents and resources that consider individual characteristics (e.g., knowledge level, prior experience, cognitive abilities, learning preferences, and cultural difference) is referred to as personalized learning or adaptive instruction. However, these considerations may not provide dynamic adaptive learning that takes into account the implicit variables, generative intelligence, such as neuro regulation mechanisms, meta-cognition, meta-emotion, and self-efficacy learning behaviors (Vandewaetere et al., 2011; Laak & Aru, 2024; Nickl et al., 2024).

The adaptation and delivery of instructional materials and resources play crucial roles in enhancing personalized learning; adaptive instruction can be traced back to thirty decades ago, it refers to an educational approach and or intervention that incorporates alternative procedures and strategies for instruction and resource utilization and has the built-in flexibility to permit individuals or different groups of students to take various routes to, and amounts of time for, learning, and acquiring or developing the knowledge and skills to complete the tasks or achieve the goals.

It is generally applied as a teaching approach that provides adaptive instruction and tutoring based on the learner's descriptive profile information (e.g., prior knowledge level, experience, background), these data could be assessed by the pre-test or post-test that led to the determination of appropriate assignment of instructional units and to facilitate the differentiation learning to meet the needs of individuals (V. S. Towle Brendon, 2003;.B. Towle & Zhou, 2024). The learner might be required to achieve a pre-set level on the mastery of the learned unit before proceeding to the next following appropriate levels. However, this type of adaptation suffers from the limitation of available time, resources, and ability to evaluate each different achievement and the implementation effectiveness. With the advent of emerging technologies, a wide range of adaptive learning systems were developed to provide dynamic personalized adaptive learning that helps learners access interactive and intelligent web-based educational system that provides intelligent tutoring and adaptive technologies (e.g., ELM-ART, intelligent textbooks, courses, exercises), to interact and collaborate with the other learners, and obtain an instant recommendation, navigation, support, and feedback (Weber & Brusilovsky, 2016; Sosnovsky et al., 2023; ; Brusilovsky, 2024; Yan et al., 2024). These systems improve the limitation in the traditional classroom settings that generally provide the same sequences for the learners irrespective of their personal variable characteristics, instead, through the adaptation, delivery of tailor-made presentation of learning materials, sequences, and offering personalized adaptive learning opportunities anytime and anywhere to meet the individual requirements. These adaptive learning systems incorporate certain characteristics of adaptability and adaptivity through the user-control and or system-control with adaptive methods, techniques, and tools; they have been developed and are inspired by the Intelligent Tutoring System (ITS) and adaptive hypermedia or other emotional adaptive learning systems (Çebi et al., 2023).

Cloud-computing is emerged with its advantages, including the autonomous, cost-effective, flexible, and reliable infrastructure, which enable the creation of an e-learning ecosystem, thus, incorporating cloud computing and crowdsourcing technologies into e-learning services in the classroom plays a significant role in supporting adaptive learning. Personalized learning, smart campus, learning analytics, teacher evaluation, intelligent tutoring robots, and virtual classrooms are only a few of the applications of educational AI that enhance adaptive learning innovation from different aspects (Tackett et al., 2018; Alam, 2023).

From the techno-perspective, adaptive learning environments are intelligent instructional and tutoring systems that developed with the application of artificial intelligence techniques (e.g., decision trees, fuzzy logic, Bayesian networks, neural networks). As mentioned earlier, learning goals, cognitive preferences, levels of cognitive abilities, knowledge mastery or proficiency, and learning experience are recognized as important factors in learning. From the adaptation by learning style, Adaptive Educational Hypermedia Systems based on Learning Styles (AEHS-LS) aiming to adapt educational materials individually to the learners, and the effect of implementation such as the system of INSPIRE system that based on Honey and Mumford learning style model (AEHS-H&M); system AMDPC based on Witkin's Cognitive Style Model and Felder-Silverman's Learning Style Model; system CS383, MASPLANG, LSAS, TANGOW that based on Felder and Silverman Learning Style Model; system MOT that based on Kolb's Learning Style Model; system PALS2 that based on Jackson's Learning Styles Profiler; AEHS-LS that based on VARK Learning Style Model; system iWeaver that based on Dunn and Dunn's Learning Style Model was evaluated, and that indicated significantly improved performance (Qodad et al., 2020; Boussakuk et al., 2020). For instance, INSPIRE represents an intelligent instruction system based on learning style, knowledge level, and learners' progress that personalizes instruction, and dynamically generates lessons that gradually lead to the accomplishment of the learning goals selected by the learner;

CS383 is an adaptive hypermedia interface and courseware that are developed to personalize the presentation of course materials to user's learning style; system iWeaver", a Web-based adaptive learning environment that implements different forms of adaptation, provides an introductory course on computer programming in accord with user's learning styles (Tsortanidou et al., 2018; Elmabaredy et al., 2020; Lestari et al., 2024; Sumarlin et al., 2024). One recent successful example is the Programming Tutoring System (ProTuS), which provides smart and interactive content, personalization options, adaptive features, and learning analytics as support for users engaged in learning complex cognitive skills (Vesin et al., 2018) are developed as an adaptive assessment tool that analyzed the concurrent validity of the Index of Learning Styles.

A wide range of adaptive systems take decisions using a single source of personalization information, some systems such as the TSAL system use two sources of personalization information: learning behavior and learning style. This interactive system takes into account learner interactions with the system, and uses learning behavior, which comprises the learning achievements or outcomes, learning needs, and time is taken to do the tasks (engagement and concentration degree) to assign the learning style and to determine the sequential presentation style and the difficulty levels of subsequent materials. Certain intelligent tutoring systems provided negotiation-based adaptive learning with the functionality of supporting learners with learning needs such as cognitive tutors.

Despite of these, prior reviews lacks of theoretical underpinnings with common defined–criteria and indicators to measure various variables, adaptive elements, approaches, specific issues and priorities of implementation, and how to incorporate them to adapt into the different models in adaptive learning systems or environments. More particularly, we reflect if it is feasible to combine as many as sources of adaptation with different methods, techniques, and tools. How the learning stakeholders can evaluate the effectiveness of these adaptive initiatives before the empirical implementation? Current research indicated that the insufficiency of a combination of more visions with transdisciplinary from different learning stakeholders to provide further adaptation; targeted adaptation is determined by performance, behavior, affection, and aptitudes of learners, and these initiatives are rarely followed by a high-quality and thorough empirical evaluation of their effectiveness.

Although, higher education institutions are increasingly interested in using data-driven adaptive learning as an innovative solution to evaluate learning effects. The actual adoption of attitudes and opinions of educational stakeholders and learning practitioners in the implementation of adaptive learning in courses remains rarely insufficient, this leads to the design of adaptive learning systems concentrating more only on the pilot tests, empirical experience of how to improve learning process based on the adaptation on learning goals, cognitive preferences, learning difficulties, teaching requirements, instead of improving learning performance based on the prior experience and current outcomes, quality evaluation of logic and sustainability, design of support in developing different types of knowledge, improvement of skill or competence.

Adaptation based on learning style, knowledge level, learning effects, psychological cognitive, and meta-cognitive strategies, in the learning environment has been considered an important area of research because of the inherent complexity of adaptation, a large number of learning models and dimensions, measurements of cognition, psychology, adaptive scaffolding, feedback, intervention methods, advanced techniques, tools and the many variables that need to be analyzed, selected when evaluating the feasibility, impacts, and sustainability of adaptation. This thesis work aims to evaluate feasible applications in the adoption of certain indicators, and measure the impacts based on these variables. It focuses on two objectives: how to design an adaptive learning companion system to improve the adaptability of auxiliary models based on learners 'cognition, metacognition and affect so as to increase the learning gains (Kautzmann & Jaques, 2019; Scheu

& Benke, 2022; Feraco, Casali, et al., 2023); reflecting adaptive learning ecosystem construction to the systemization of multiple serviced-oriented adaptive learning systems, which favor the development of system capabilities in the integration of expertise.

Although there have been increasing attempts to build the mechanisms of adaptive learning to enhance learning and maximize impacts, there is a paucity of carefully designed, sufficient experimental evaluation of the effectiveness, and proposes the adaptation based on applied learning science and adaptive learning analytics could be in the prioritized list than proposing novel intelligent techniques with questionable benefits (Brusilovsky et al., 2022a; Sarıyalçınkaya et al., 2021a). Another challenge is the insufficient experimental evaluation of the utility and impacts of variables that are usually considered to determine the forms of adaptation. Some crucial factors (e.g., epistemology, didactics, ethics, meta intelligence) should be taken into account when evaluating the system's adaptivity and learning adaptability (Mavroudi et al., 2018; Mirata et al., 2020; Mavroudi, 2023; Gupta et al., 2024).

The results of studies in the regard of the adaptation, which based on measurement of individual adaptive learning with traditional models are non-conclusive, remains the limitation in the confidence of generalizing the learning effect, as it faces the challenges of small samples, small-scale and short-term applications (Truong, 2016; Alshammari et al., 2015;Hmedna et al., 2020; El-Sabagh, 2021). Considering the aspects of adaptivity and personalization, evaluation methodologies have become a complex area that requires multiple assessment techniques such as learning analytics, biometrics to be combined, and performed in heterogeneous ways (Chowdhury et al., 2023).

The case has been made that evaluation through experimentation or tests with self-regulated learners has been shown to be significant to reflect on the improvement of learning systems, as it generates evidence of usability, feasibility, utility, and acceptability. Experimental evaluation is chosen as the main method in this study for assessing the feasibility of different forms of adaptation, particularly through pilot testing conducted to answer the research questions, it has specific objectives and hypotheses. It plays a role in determining the advantages, effectiveness, and usability of learning application by observations, analysis, and reflection in a controlled approach in blended learning environment. In addition, the appropriateness of this evaluation approach can be justified by the evidence of the target audience, because the main source of data is usually generated from user-system interaction (Mulwa, 2012; Luan et al., 2020; Emond, 2021; Mohammadi et al., 2024).

This research seeks to address issues in: how the development and evaluation of didactics, adaptive learning, analytics frameworks, models and mechanisms, could favor effective adaptation in the construction of a deeper learning ecosystem; the reflection on the logical, feasible, and sustainable impacts behind the mediation tools that underpin the coordination for future implementation work in the construction of adaptive learning environments. Are there aspects of theoretical reference models that are not investigated thoroughly that shall enable more effective and deeper learning in projects and management? More elaborated and careful project plan in the conduction of empirical evaluation /testing of learning systems or applications should be needed. These investigations are highly relevant to the future integration with feedbacks and adaptation mechanisms into the learning management ecosystem in higher education institutions (HEIs).

1.3 Research Objectives & Questions

Since the learning performance, quality and user experience have been identified as the crucial concerns and indicators of implementation of pedagogy innovation and adaptive learning. The key objectives of this thesis are to provide a commonly recognized definition of adaptive learning and to evaluate the sustainable impact based on the Education 5.0 paradigm. With the respect of this,

this study explores the critical components, explains the mechanisms and the rationale of adaptive learning environments. Furthermore, the theoretical underpinnings, the indicators, the techniques of specific mechanisms and models are also investigated and interpreted. As a result, several frameworks and solutions are proposed for adaptive learning practitioners and research communities.

In order to reflect on what types of features enhance the conception of adaptive learning environments and maximize the impacts of implementation, Chapter 2 identifies the contexts, learning objectives, didactic principles, knowledge components, learning strategies, adaptive mechanisms, and users' requirements that contribute to the logic design of hybrid flexible learning environments, adaptive learning scenarios, and collaborative activities. Simultaneously, it aims to evaluate how learning stakeholders interpret the changing complex phenomenon of adaptive learning. Furthermore, how these mechanisms should be developed appropriately so as to stimulate cognitive activities, to activate individual schemas, to promote knowledge acquisition and learning transfer. Chapter 3 explores how to construct and evaluate the impacts of adaptive learning ecosystem. The highlight includes the discussion of the roles and transformative potentials of emerging educational AI technologies and human (meta) intelligence in enabling adaptive learning. The gradual transformation and promotion of adaptive learning: from teaching-centric to user-centric, hybrid flexible ecosystem, as well as personalized adaptive learning environments. A synthesis of review of the prior theoretical foundations and empiric evidence across disciplines is carried out, so as to derive the design principles of feasible modelling approaches, techniques, and tools. Simultaneously, it reflects on the impacts of various adaptative learning elements and measures in enhancing learning adaptability, as well as system adaptivity, compatibility and durability. Eventually, it assesses in how and when the target audience benefits from the development and the integration of these models within the methods of trans-disciplinaries.

Chapter 4 presents the creation of a taxonomy of learning analytics and evaluation. It aims to resolve why or when the adjustments of methods, techniques and tools with respect of specific or combined adaptive parameters, should influence the implementation of particular adaptive projects. Artificial intelligence enables learning innovation stakeholders (i.e., designers, developers, engineers, and practitioners) to design adaptive tools to interpret (meta) cognitive processes, provide different types of learning supports, scaffolds and feedbacks. These feedback loops may be designed and proposed to meet specific needs, for instance, real-time cognitive process feedback or metacognitive instructional scaffolding, which may improve knowledge acquisition, self-regulation behaviors and strategies. Encouraged hints, affective scaffolds, learning style scale(s)-based resources recommendation may enhance learning experience. Adaptive prediction, sequences and navigation may optimize cognitive activities, learning paths. Adaptive corrective hints, learning remediations, procedural feedback might be developed based on the performance, the learning difficulties and risks that detected in the exercises or practical work, these may improve the problem-solving processes and conceptual understanding. Interactive Q&A feedback and metacognitive support based on inquiry learning may improve knowledge acquisition, mastery and transformation. Simultaneously, feedback mechanism may also be designed for meeting pedagogical goals and curriculum innovation, it may also improve teaching design, course evaluation, and didactic sequences. Furthermore, the feedback results may also allow higher education innovation institutions to acquire the information about the newly generative learning from learners, formulate the effective policies, develop more beneficial learning technologies, promote the learning engagement, and improve the attractiveness of education.

Chapter 5 illustrates the key objective and significance of specific implementation based on the combination of the results from above literature reviews and adaptive project background. With the respect of prior experience, educational practitioners should be able to formulate logically feasible protocols from heterogeneous dimensions, levels, and to set corresponding criteria and indicators: learning performance and quality measurement and evaluation. The smart learning environments construction take into account the benchmarks such as usability, ease of use, flexible compatibility, adaptivity, adaptability, and sustainability within contexts and across levels of domains. It manages to answer the question of situ construction of adaptive learning, that is, where and how to achieve specific goals, maximize learning effects, enhance engagement and user experience in learning platforms.

Chapter 6 describes and analyzes the specific pilot test module and the collected learning data. The aim is to verify effective learning theories in authentic environments and situations. The hypotheses are proposed for the analysis of learning performance and quality. To whom, and how the developed content, application and feedback tool are employed in the pilot test, the obtained information and data (e.g., learning achievements, learning difficulties, learning progresses, cognitive strategies) are classified and interpreted, in where and which should impact on sequences of curriculum, optimization of learning paths, adjustment in levels of difficulty, thereby further improve overall didactic design and learning performance.

Thus, this dissertation aims to address the following key research problem and sub questions, as depicted in Figure 1.

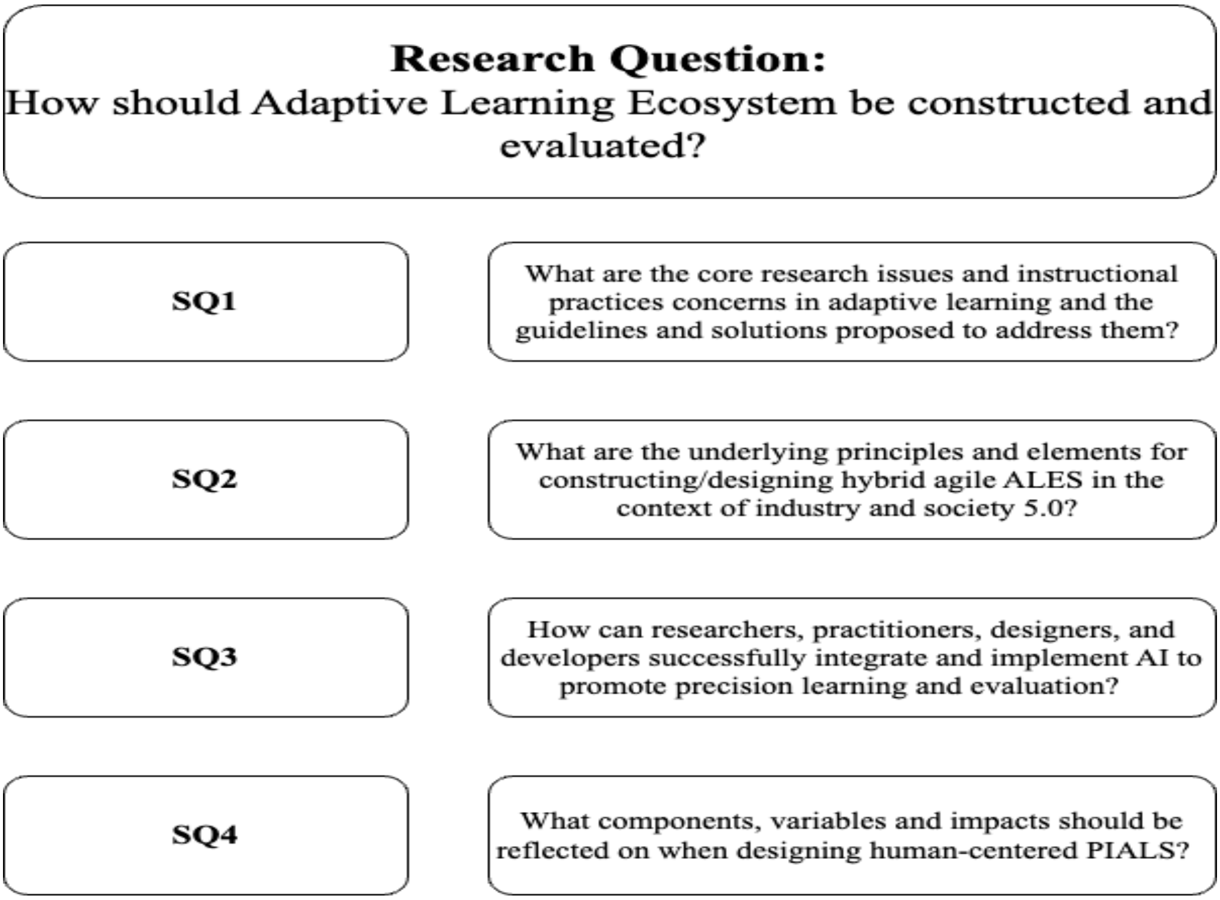

Figure 1. The research questions

RQ: How should adaptive learning ecosystem be constructed and evaluated?

The studies highlight the design principles and adaptive features and demonstrate the relevance of various mechanisms in mediating adaptive learning, and stimulating (meta) cognitive processes in heterogeneous circumstances. The investigation in Chapter 2 resolves the design concerns and raising issues in the didactic engineering that may influence learning performance and quality.

To answer the RQ, this study began by reviewing the literature on the theoretical foundations of adaptive learning. The couple between learning theories and learning styles has been the primary concern in pedagogical and didactic engineering. By illustrating what the precisely learning mechanisms shall be feasibly designed and how these interventions could be efficiently implemented in the specific contexts. Thus, on the basis of reviewing theoretical models, the first sub-question was crafted to depict a comprehensive didactic framework, which should guide the feasible construction of adaptive learning mechanisms in stimulating cognitive schemata and learning activities.

SQ1: What are core research issues and underlying instructional practices concerns in adaptive learning, and the guidelines and solutions proposed to address them?

From the literature review, it was understood that a wide range of studies in the field have integrated traditional models and advanced techniques to identify the learning effects and improve overall performance. However, there is lack of consensus of why these guidelines or solutions can be adopted logically. Moreover, the complexity of changing environments and phenomenon of learning lead to different understandings and expectation of learning effects, and implementation challenges of instructional practices. Thus, develop a comprehensive didactic engineering framework that illustrate how adaptive learning mechanisms and (meta)cognitive activities could be constructed and fostered based on specific objective of knowledge acquisition, learning needs and feasible instructional technologies become the priority of reviews.

Given how rapidly social innovation and AI technology are involving, there is still a need for research endeavors to develop principles and specific support for founded on theoretical evidence and empirical evaluation. In light of this, a critical synthesis of reviews that established for the reflection of the construction and impacts of adaptive learning ecosystem is conducted. Therefore, SQ2 was designed as follows:

SQ2: What are underlying principles and elements for constructing hybrid agile adaptive learning ecosystem in the context of industry and society 5.0?

The construction and impact of an adaptive learning ecosystem

There has been implementation to acknowledge emerging AI technologies that is pervasive and can promote precision learning. What are the adaptive learning design principles, methods, components, and techniques, and if the improved system embedded with supplemented modules could enhance the capacity of system adaptivity and learning adaptability? The classic models and mechanisms include the generic models such as user model, domain knowledge model, instructional model, pedagogical management module, adaptive learning engine, presentation model; the mechanisms of recommendation, feedback and intervention. These added modules may include motivation model, emotional model, personalized learning analytics model, metacognitive auxiliary model. These adaptive learning technologies and mechanisms could be integrated into AI-enabled adaptive learning ecosystem in the context of higher education 5.0 paradigm to offer an inclusive lifelong learning and management.

This part of studies therefore looked into the practical benefits and efforts of emerging adaptive learning technologies and current issues that need to be addressed. The learning analytics, (big) data and process mining techniques have been employed to facilitate adaptive education and precision learning. SQ3 was therefore designed as follows:

SQ3: How can researchers, educational practitioners, designers, and developers successfully integrate and implement AI and machine learning technologies to promote precision learning and evaluation?

The question proposed in this part of the investigation is to measure the impacts and to reflect on future implementation criteria and assessment indicators. How these actions should favorize the adaptive learning, tutoring, recommendation and intervention in the specific adaptive program. This relates in how to improve personalized service-oriented adaptive deep learning experiences, based on the synthesis of reviewing previous theoretical research frameworks and empirical evidence. With the respect to the diverse models and mechanisms (e.g., the domain model, the instructional model, the learner model, the user interface model, the management model and the adaptation model), measuring the implementation impacts and quality of the project, these indicators include learning performance, behavior, preferences, cognitive states, technology acceptance and risks. It provides a common reference framework of learning analytics-driven adaptive learning and intervention system development.

SQ4: What components, variables, and impacts should be reflected on when designing human-centered personalized intelligent adaptive learning system (PIALS)?

Sub-question 4 aims to verify learning and theories based on specific context and the evidence in the authentic learning environment. The learning data collected within Module D of the project ET-LIOS, selecting and classifying the adaptive parameters, evaluating and developing specific methods, techniques, and tools used to benchmark the effectiveness, feasibility, and sustainability from the perspectives of pedagogy innovation and didactic engineering. This involves issues such as protocols, types of variables, datasets, learning performance, learning outcomes, and quality. Is data collection based on the certain variables useful for the measurement of learning effects and impacts? How the logical basis for learning analytics, data mining techniques, automated evaluation and formative feedback can be developed? How can curriculum content, learning support, feedback and intervention mechanisms be designed based on these types of data sources and learning outcomes? And how the adaptivity features enrich the design of assessment devices so as to enhance the effectiveness of individual learning activities and sequences? Eventually, this thesis reflects on how the learning adaptability could be underpinned by the implications of personalized learning analytics, and the (meta) cognitive auxiliaries and scaffolding? Why and when these adaptive models and techniques should increase attractiveness, effectiveness, and feasibility within the case-by-case or in general level? Where are the interplays between learning systems and an ecosystem, and where are the impactful areas and directions for future work?

1.4 RESEARCH METHODOLOGIES

The thesis examines issues, which require further elaboration of logically feasible design, measurement and evaluation of sustainable impacts of intelligent adaptive learning.

Since the scope of this study related mainly the construction and impact reflection of adaptive learning mechanisms, the work began by reviewing the previous literature to identify and classify fundamental learning theoretical models and the relevant concepts. Furthermore, the limitations, the issues and the design concerns in viable design guidelines and adaptive learning methods are highlighted. Then, a design of a comprehensive didactic framework, which illustrated the processes of knowledge acquisition, the construction of adaptive learning mechanisms, and the implementation impacts of adaptive features enriched learning activities and systems is eventually proposed in Chapter 2. As an instanton of that framework, different forms of adaption based on both domain-general context and learner-specific knowledge are explained.

The main goals of designing this comprehensive didactic framework are to:

• Reveal the (meta) cognitive activities in facilitating the processes of knowledge acquisition and learning transfer.

• Construct the logically feasible learning mechanisms by taking into account the relevant adaptive principles in the specific circumstances.

• Evaluate the performance and effects of adaptive features in learning and instruction systems.

A conception of dynamic adaptive learning conceptual framework, which described /illustrated specific adaptive learning principles, elements, techniques are proposed in Chapter 3. It aimed to revolute the construction and maximize the impacts of adaptive learning environments. As an anchor of designing adaptive learning environments, different impacts of adaptation based on indicators are explored.

The main goals of illustrating the conceptual framework of adaptive learning:

•Interpret the term of adaptive learning according to specific contexts.

•Decode the transformative potential of adaptive learning technologies in the contemporary educational paradigm.

•Evolute the prior system models by taking into account its different components.

•Develop the supplementary models to promote the adaptation and maximize the impacts.

•Draw the synthesis of insights and conclusions about the evaluation guidelines to favorize future implementations.

A taxonomy of learning analytics, which classified diverse adaptive factors is proposed in Chapter 4. The main objectives of creating the taxonomy:

•Identify various forms of adaptation and techniques based on adaptive elements such as performance, behaviors, learning preferences, personal traits, cognitive status, technology acceptance, learning risks.

•Utilize the results of synthesis of review in learning analytics to recommend adaptive activities, develop interventions strategies, improve feedback mechanisms.

• Evaluate the added effects and values of the adoption of artificial intelligent techniques, and how these tools differ when providing adaptation based on a single dimension or in combination of different elements.

With the respect of the prior knowledge and experience, main tasks identified in the project ET-LIOS[5], relevant protocols for designing a learning application that enable data tracking and intervention by feedback are developed in Chapter 5 and 6. It verifies the relevant hypotheses with pre-set adaptive parameters and learning variables.

A pilot test is conducted to improve the execution and the studies. The main objectives of testing:

• Validate the feasibility of the present implementation conditions, technical issues related to the developed system, data collection reliability and consistency, the difficulty level of learning materials, project duration, and evaluation issues.

• Measure the learning effects based on learning success, learning paths, learning difficulties, and how learner behavior and strategies differ and influence learning progress.

• Evaluate the proposed approaches, the impacts, the quality, and their interplay with the issues of adaptivity and sustainability.

• Develop the capabilities of the companion system or applications to accommodate learning by providing the indices, suggestions, mistakes correction, remedial measures, or feedbacks.

1.5 RESEARCH CONTRIBUTIONS

The research reported in this thesis brings several contributions to domain knowledge and models construction in the field of adaptive learning environments. These contributions include the design of a didactic guidance framework, an implementation conceptual framework, a taxonomy of adaptive learning analytics, a multimodal assessment model and feedback loops.

[5] ET-LIOS is a higher education hybridisation project dedicated to the Industry of the Future. During the health crisis, teaching had to adapt to the severe constraints of confinement and gauges. Distance learning and hybrid courses were developed to ensure continuity in teaching. To support these new ways of teaching, it is important for universities to coordinate their efforts to develop the tools, resources and infrastructures they need to best meet the needs of users. Technological teaching is all the more of a challenge when it comes to hybrid teaching. The need for access to industrial machinery and equipment is crucial and decisive.

The contribution in Chapter 2 relates to the proposed comprehensive didactic framework, it can be used as a reference framework or interdisciplinary model to design mechanisms of adaptive learning environments. Within the overall comprehensive didactic framework, (meta) cognitive processes, adaptive learning mechanisms, relevant specific learning activities with intelligent adaptive features have been explained. The didactic framework has been essentially designed as the guidelines and solutions to develop a set of adaptive and adaptable learning mechanisms to stimulate internal cognitive processes, and to forester external learning opportunities.

The contribution in Chapter 3 relates to the reflective works of the construction and impacts of adaptive learning ecosystem, which takes into account their components, approaches, techniques, and tools. Two supplementary components and models are necessary for wide range of personalized adaptive learning environment. In addition, the issues of usability, accessibility, combability, adaptivity, adaptability and sustainability are evaluated. The relevant adaptive learning principles, elements, techniques are also covered in the synthesis of review.

The contribution in Chapter 4 relates to the creation of a taxonomy of learning analytics and multimodal evaluation model. It can be used to inform practitioners, learning stakeholders to use the results of Learning Analytics (LA) and Educational Data Mining (EDM) to develop adaptive learning and intervention systems design, to maximize adaptive learning effects based on certain adaptive parameters. This chapter indicates the importance of specific methods and explores the AI potentials for precision learning, tutoring, and evaluation.

The major contributions of above review work, concern from the elaboration of conception design and performance evaluation, and from the "thorough "synthesis and "reporting" of learning analytics results with a focus on joint actions of didactic engineering aspects, and the system adaptivity and learning adaptability when providing different forms of adaptation. The key factors of cause-effects of learning mechanisms concern in the perceived agility, feasibility, usability, accessibility, adaptivity, and adaptability, are taken into account when evaluating the system' capabilities in providing dynamic adaptation and feedback loops.

The major contribution in the project's pilot test, relates to the construction and development of the learning applications that allow the tools to adapt in learning requirements of each learner, it allows the memorization of dynamic learning trajectories, provides automatic generation of hints, prompts and reminders of forgetting or un-mastery areas based on the errors made by learners from practical work. The major contribution in the conduction of pilot test relates to the stealthily tracking, analyzing individual learning trajectories' data, while adaptively adjusting the design, presentation of learning materials, activities, and difficulty levels from meso and macro perspectives. Furthermore, providing additional cognitive and metacognitive auxiliary, strategies, feedbacks whenever it is required to implement intervention from the micro perspective based on the validity of applied adaptive learning science.

The major contribution in the evaluation work on learning data analytics that was used to assess the perceived value, sustainability, and impact, using standard metrics and measurements, and to investigate the interplay between user experiences such as perceived sense of usability, usefulness, acceptability, attractiveness, and performance.

The pilot test carried out to address SQ4 relates to the measurement of learning results and influences of specific project implementation based on the criteria and indicators with the regard of factors and variables in the contexts.

The results and contributions are summarized as follows:

• Investigate the adaptation based on the processes of problem-solving dimensions and the effects on corrective feedback, task-specific hints.

• Explore the learning success, learning progress, misconception, risks, self-regulated learning (SRL) behaviors, strategies, to interpret the performance and quality.

The results of this study offer more theoretical underpinnings for designing adaptive feedback loop from the evaluation of knowledge acquisition, the construction of learning projects, the implementation of instructions in the different stages within specific context. For brevity, the main contributions of this work come from the careful design, compartmentalization, analysis, and implementation of experiments and evaluation, and thorough stealth tracking, reporting, and assessment of quantitative results of experiments, focusing on the aspects of the learning experience, impact, and sustainability when evaluating the provisions of different forms of adaptation. When measuring and evaluating learning effects and quality, these factors are considered: learning progression, motivation, and engagement. The experimental results can provide more evidence and experience of designing personalized adaptive learning contents, sequences, assessments, tools and activities to meet the diverse and unique needs of self-regulated learners in e-learning systems.

1.6 Thesis Structure

There are two main parts in this thesis. First part provides the integrative perspective of adaptive learning through reviewing the literature. Second part presents the life cycle of the project and establishes the empirical evidence and experimental foundations. It is comprised of seven chapters clustered into four categories addressing the research questions and objectives. Figure 2 summarizes the highlights of the thesis structure and conducted work.

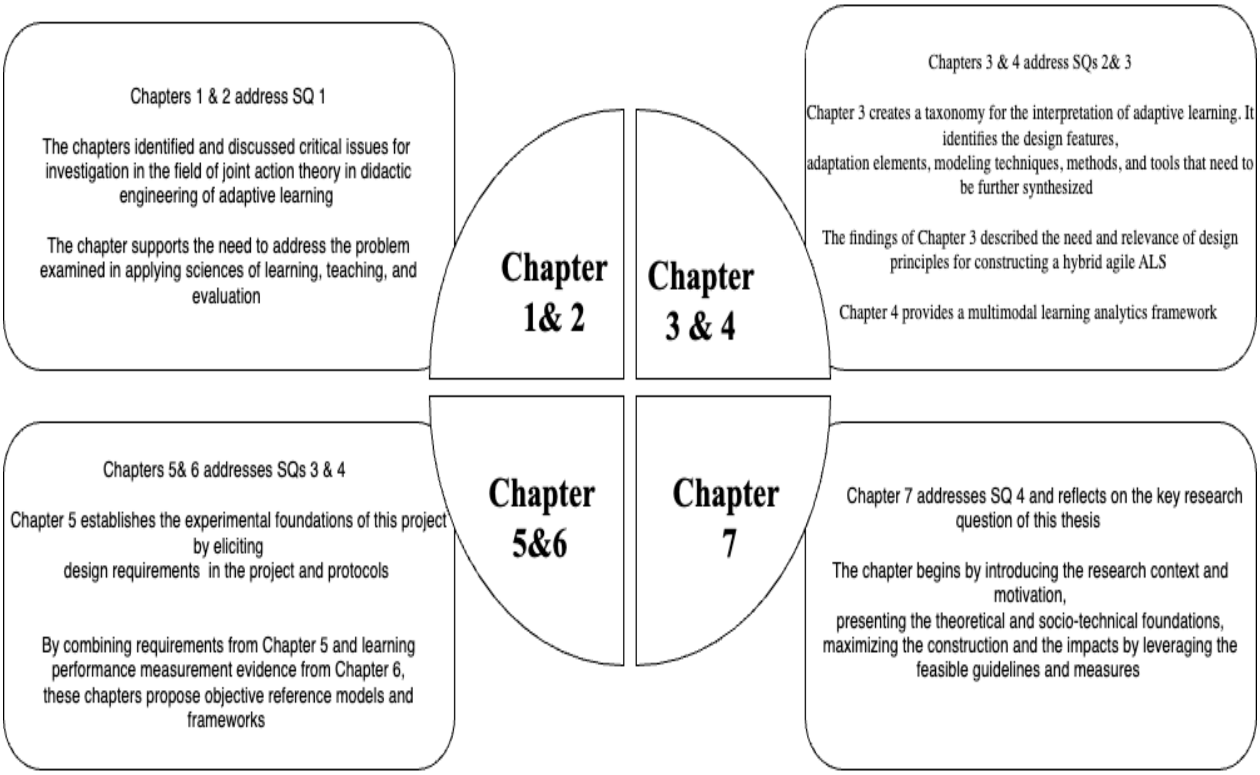

Figure 2. The highlights of thesis structure and conducted work

This thesis is comprised of seven chapters including research context.

Chapter 1 introduces the research background, general research questions, contributions, thesis structure of current work, and implications for contributions and innovation in this thesis.

Chapter 2 reviews the learning theoretical models and learning styles scales. The arising concerns of issues relate to the adoption of models and limitations are also discussed.

The purpose is to elucidate how theoretical foundations relates to the spheres of didactic engineering design and innovation. Second part of this chapter explains when the incorporation of adaptive and adaptable learning mechanisms, respectively external learning opportunities, adaptive learning activities, and internal (meta) cognitive tools or self-efficacy activities, significantly facilitate cognitive processes to acquire knowledge components. And it explores why the cause-effects of intelligent features-enriched open (personalized) adaptive learning environments construction need more evaluation and integration of adaptive frameworks.

Chapter 3 addresses three key issues that need to be elaborated in the currently existing literature review of adaptive learning. There is still a paucity of a synthesis of reviews on how to create a conceptual framework of adaptive learning within the context of industry and society 5.0.

Firstly, this study introduces the general research background and creates a taxonomy to explain adaptive learning models within different specific domains. The separated effects, limitations, and expected work in the conceptual framework are also discussed. Secondly, a critical synthesis review is conducted to investigate intelligent tutoring and adaptive learning design features, components, approaches, techniques, and tools. The objective is to provide evidence and knowledge in evaluating the construction impacts of system adaptivity and learning adaptability within the contexts. Moreover, the research design is underpinned by the selective criteria of inclusion and exclusion. Eventually, this study emphasizes the highlights in the research of metacognition monitoring and adjustment in Self-Regulated Learning (SRL), Co-Regulated Learning (CRL), and Socially Shared-Regulated Learning (SSRL). The purpose is to facilitate the construction of adaptive deep learning in hybrid flexible learning environments in the context of higher education. The current existing reviews lack of contributions in integration of adaptivity and adaptability to create dynamic personalized, adaptive regulated learning in hybrid flexible environments. The purpose of this chapter is to provide evidence on how best to construct metacognitive auxiliary models.

The main contributions include two aspects: a standard concept reference framework of adaptive learning by examining adaptive learning modalities in diverse contexts; a dynamic implementation framework, based on investigation and evaluation of adaptive learning environment's adaptivity and users' adaptability according to specific situations.

Chapter 4 reviews learning analytics and evaluation approaches. The reviews focus on three objectives: the interpretation of these two terms: learning analytics and educational data mining techniques; the creation of a taxonomy of the metrics of learning analytics and their corresponding machine learning techniques; the implications and challenges of multimodal learning analytics and evaluation of CAMM (Cognition, Affection, Metacognition, and Motivation) processes that facilitate personalized adaptive regulated learning. The contribution of this chapter is to provide the framework of multimodal learning analytics and assessments. The interpretation of terminologies and their implications for future innovation in deeper learning are also covered. The review of this chapter is to provide evidence for the construction of personalized adaptive learning, instruction, and assessment models.

Chapter 5 introduces the context and purposes of project ET-LIOS, and the participants in the joint action of design, implementation, and evaluation are also presented. This chapter then highlight the dynamic roles and influences of heterogeneous groups of stakeholders in specific programs such as personalized intelligent tutoring system in flipped classroom learning settings, adaptive learning management system in smart campuses, and hybrid adaptive learning in open-ended learning environments. The chapter proposes an implementation Gantt Chart: to elucidate stakeholders' involvements in a holistic process of the adaptive learning environment. Current research lacks a critical synthesis review of the stakeholder's interests and involvements in the three aspects: didactic engineering, adaptive learning systems, and adaptive learning ecosystem.

Chapter 6 presents the measurement results of learning performance and quality in module D of project ET-LIOS. The data tracking and mining focuses on factors such as learning performance, probabilities of knowledge mastery, learning behavior cues, cognitive and metacognition strategies, engagement, and motivation. The measurement and evaluation of variables, include the number of trials of success and errors, the time engaged during the class and after the class, and the number of inquiries from a companion. The limitations of the work are revealed. Another contribution of this empirical work is to formulate a measurement and assessment framework: to summarize the indicators, criteria, and variables for learning analytics, formative and summative assessment. Chapter 7 overviews the thesis work, objectives and research significance; summarizes the proposition and contribution in each chapter. This chapter discusses the findings and implications, illustrates the research efforts considering implications, and explores how the dynamic adaptive learning processes and relevant methods can be charted. A generic reference framework for the construction of adaptive learning ecosystem is proposed. The main contribution is to integrate the mediating tools for a dynamic evaluation related to construction and implementation impacts of adaptive learning and future innovation.

CHAPTER 2: THE THEORETICAL FOUNDATIONS AND DESIGN PRINCIPLES

2.1 INTRODUCTION

This chapter reviews the key learning theoretical frameworks to understand the process of learning and guide the design of instructional practices. It begins with interpreting the relevant principles on several theoretical models and identifies the influential contributions and the specific issues in the construction of adaptive learning and instructional environments. Since learning needs are distinctive, and interaction methods are diverse, the integration of both theoretical models with intelligent tools into teaching practices becomes critical in providing adaptive learning experience. These models and techniques are highly influential in learning practices and humanity's transitions. Thus, this chapter aims to addresses specific question: "What are the core research issues and instructional practices concerns in adaptive learning, and implementation guidelines and solutions"? This chapter identifies and reflects on critical issues for investigation in new didactic approaches of adaptive learning engineering.

Thus, comprehensive didactic framework is proposed to support the interpretation, and reframing of what constitute in adaptive learning, what are the requirements, the principles, the guidelines should be included while designing and developing adaptive learning environments. A discussion of the implications of these models in promoting knowledge acquisition, activating meaningful learning mechanisms, and designing instructional practices of personalized adaptive learning is also developed. As a conclusion to this chapter, the interplay among theoretical models and their contributions to the construction, the implementation and the evaluation of adaptive learning environments are elucidated.

2.2 LEARNING THEORIES

2.2.1 Introduction

Learning has been defined and interpreted in different ways and perspectives by educational theorists and learning theorists. These explanations include the environment in which learning occurs, the methods that affect learning process, the behaviors and efforts that influence learner's knowledge components acquisition and cognitive levels change. Although, many learning theories have certain common elements, the ubiquitous learning, and the constantly changing environment influence the redefinition and reflection of learning itself. Teachers as learning facilitators, who can organize the learning content to be learned or taught, the context or environment in which learning occurs, and the evaluation of learners'characteristics and learning needs.

Learning effectiveness from learners' perspectives depends on many variable elements, including cognitive domain, psychomotor domain, emotion domain, and metacognitive domain. These factors, including motivation, engagement, knowledge, skills, affective state, and attitude change are interconnected, and they have been influential in academy buoyancy and learning outcomes. For instance, motivation is an important factor that affects learning performance, it can be reflected from learners' expectancy, value components, change in cognition, emotion, and behavioral engagement in certain aspects (Fredricks & McColskey, 2012;Frenzel et al., 2023). The other factors related to motivation and emotional regulation are learners' sense of feelings, self-evaluation, self-efficacy and co-value. Händel et al., (2020) stated that the challenges of emergency remote learning include human's socio-emotional perceptions, especially stress-related emotions (anxiety, tension, and overload), as well as social and emotional loneliness. All of these socio-emotional factors could influence cognitive processing and learning performance.

There are different perspectives to interpretate how knowledge components are acquired. Perspectives including empiricism, rationalism, positivism, post-positivism, have been emerged over the years and continued to influence the development of learning theories. Empiricism emphasizes that experience is the main source of knowledge and that knowledge is obtained as a result of interactions with the learning environments mainly through sensory channels. Rationalism emphasizes that knowledge is derived from deductive reasoning, information retrieval and arises through the mind without considering the senses. Positivism based on solid facts that are objective instead of subjective interpretation. Although, it is accepted as the primary paradigm in researching educational reality to prove that phenomena from the field of social sciences and humanities are equally subject. It lacks of scientific verification in the theory, which holds that all knowledge is either true by definition or positive meaning posteriori facts derived by reason and logic from sensory experience. Post-positivism integrated views of positivism and other theoretical learning foundations. It is a metatheoretical stance that amends positivism and has impacted learning theories and practices due to its intuitive, holistic, flexible features. It argues that theorists can be interpreted, reflective, integrated for the evaluation of learning effective on the basis of personal traits, epistemological foundations, and various factors such as learning hypotheses, biases, normative, cultural, effective commitments, sense of socially-shared responsibilities etc., These perspectives are interconnected and they have been influential in contemporary learning.

The complexity of learning has led to the development of fundamental theories or schools of learning: behaviorism, cognitivism, constructivism, connectivism and social constructivism. Although there may exist some common elements among these theories, they differ in their interpretation and conceptualization of learning. These theories are described in the following sections because of their relevance and importance in describing and understanding the concept and the practice of adaptive learning.

2.2.2 Behaviorism

The role of behaviorism is to study human behavior, and it may ignore the learning process performed by consciousness or mentality. This learning theory emphasizes the adoption of objective and experimental methods to investigate the formulas and law between stimulus and response, and how this association can be strengthened. It advocates that learning occurs through the response to an external or internal change in human behavior elicited by stimuli. Watson was the father of behaviorism. He advocated objective methods such as observation, conditioned reflexes, oral presentations, and tests. Reward and punishment represent one of the key principles of this theory. Previous behaviorists suppose, however, that the learner is a passive recipient of experience or knowledge from the stimulus of environmental factors such as the instruction from the expert or teacher. New behaviorists begin in focusing more on the holistic and purposive nature of the behavior of learners, including their motivation and cognitive processes. The evaluation of learners' knowledge is critical to determine effective instruction with preset approaches. Learning content or paths can be arranged in a pre-sequenced order, learners could use instructional hints, cues, remedies, or other types of feedback to stimulate the appropriate response and reinforce the learning of the target responses.

The learning environmental factors and other factors from learners themselves influence learning remains insufficient in discovery and association. The theory of Edward Toleman, describes the relationship between behavioral and experimental variables by applying the formula: B=f (S, P, H, T, A). “B” represents behavioral variables and “f” represents experimental variables such as environmental stimuli, training, age. He also proposed mediating variables, including both demand and cognitive variables. It is the factor that links the experimental and behavioral variables, and associates them. Edward Tolman developed a sign learning theory, which suggests learning as the acquisition of knowledge through meaningful behavior. He was influenced by Gestalt psychology, with the Sign-Gestalt as the central concept of neo-behaviorist theory, which presents a bridge to cognitivism. He believed that learning was not simply through practicing the trial-and-error, the importance is the recognition of situations, forming an isomorphic cognitive map (Tolman et al., 1946). This contrasts with Edward L. Thorndike's Law of Effects, which emphasizes repetitive learning through the trial-and-error for the acquisition of knowledge or the ability in solving the problems (Thorndike, 2017), and emphasizes the importance of meaningful learning in flexible situations. The Law of Effects is the foundation of instructional principles in operant conditioning. New behaviorist theorists have been influenced in varying degrees by operationalism. Skinner (1938) introduced the concept of reinforcement into the law of effects, developed the theory of operant conditioning or instrumental conditioning, which emphasized the positive and negative influence of humans' repetitive behaviors (Skinner, 2014; Skinner, 2016).

Procedural learning, is based on behaviorism, it emphasizes the learner's self-paced learning approach through sequences and certain feedback. These strategies may be useful for memorizing, illustrating, strengthening, and applying particular types of knowledge such as sequences, logic, and reflection. However, the development and recording of learners' competence such as critical thinking and creativity might not be well elucidated by behaviorism.

2.2.3 Cognitivism

Cognitive science has prompted learning theorists to emphasize the cognitive and mental processes for the acquisition and optimization of knowledge, such as the competencies of problem-solving, insightful learning, learning transfer, critical thinking, productive thinking, and metacognition. The metaphor of the mind as a computer can be used to describe cognitivist theories including the theories of Gestalt, information processing, cognitive load and flexibility theories, cognitive semiotics. Gestalt theorists, including Kohler, Wertheimer, Koffka, and K-Z Lewin emphasized knowledge acquisition and insightful learning from a holistic perspective rather than from the accumulated elements. The Gestalt school of learning believes that learning should break the conventional stereotype. Teachers as designers and facilitators of meaningful learning, should apply in more meaningful and creative ways to represent the knowledge, allow learners to solve problems through learning transfer, and gain higher-order thinking skills.

G.A Miller, the father of information processing theory. This cognitive development theory uses computer processing for the working of the human brain. It is an approach for the cognitive development studies of the operation mechanism of human information processing systems that aims to explain how information or knowledge is absorbed, structured, retrieved, and encoded into memories. The principles of cognitive development theory, including dual encoding, memory capacity, signal detection, and active processing. The Picture Superiority Effect (PSE) refers to that pictures can be remembered better comparing with the words, learners should be able to register and retrieve the critical information to practice and encode into long-term memory (Paivio & Csapo, 1973; Nevin, 1969). Cognitive load theory emphasizes the importance of developing long-term memory through training short-term memory and transferring it to working memory. The limitation of cognitive load theory might be that relies on the instructional design. Whereas, the cognitive flexibility theory focuses on the nature of learning in complex and ill-structured domains. Jehng, (1990) stated: “By cognitive flexibility, we mean the ability to spontaneously restructure one’s knowledge, in many ways, in the adaptive response to radically changing situational demands. This is a function of both the way knowledge is represented (e.g., along multiple rather single conceptual dimensions) and the processes that operate on those mental representations (e.g., processes of schema assembly rather than intact schema retrieval)” (Hu & Spiro, 2021).

As human often differ in their characteristics and traits, learning can be interpreted as learners’ flexible cognitive construction, and knowledge transformation processes. Both behaviorism and cognitivism, are the basis of notion that external and internal factors can enhance learning. In the design of intelligent adaptive learning models, the instructional activities are sequenced, learning paths are optimized, unnecessary information are minimized, and learning can be reinforced by collecting feedback and experiences from the synthetic agents in different contexts.

2.2.4 Constructivism

Constructive science has emphasized the application of the learning theories into didactic practices so as to favorize learning experience and knowledge acquisition. The principles of constructivism indicated that learning relies on the knowledge that individuals already possess, that new ideas occur when individuals adapt and change their old ideas, that learning involves the invention of ideas rather than a mechanical process of accumulating knowledge, and that meaningful learning occurs through rethinking previous experience and drawing new conclusions. Constructivism is the internal cognitive mental process of developing schemata from the individual learner's interpretation of experience. Constructivism is considered to be an extension or part of cognitivism, but it does not emphasize that knowledge exists independently of the learner's mind through social mapping, but rather that knowledge is an experience that results from the learner's interactions with the learning environments. Learners interpret, reason, analyze and reflect on their own experiences.

The theory underlying cognitive constructivism is developmental psychology. The principle is that the nature of cognitive development in learners at different stages promotes the active construction of learning. Piaget, (2009) claimed that the essence of intelligence is adaptation. Adaptation is a state of equilibrium in which the learner interacts with the environment and gradually construct a cognitive structure about the external world. The development of intelligence is a process of continuous construction and refinement of cognitive schemas. Piaget stated that the learner is able to respond to external stimuli in one way or another because he or she is able to assimilate the schema of the stimulus. The principles of Piaget's generic episiotomy take the consideration of the learner-environment interactions in the processes of assimilation, accommodation, and adaptation. Piaget stated that "intellectual behavior is dependent on both assimilation and accommodation, from an initially unstable equilibrium to a gradually stable one". This evolving equilibrium, the process of disequilibrium, is the process of adaptation, forming, and developing cognitive schemas.

Mezirow, (1997) argued that transformative learning is the constructivism of adult education, a process that affects changes in frames of reference, develops autonomous thinking, and affects adaptive performance. Adults have acquired a coherent set of experiential associations, concepts, values, feelings, and conditioned frames of reference that define their lifeworld.

Constructionism focuses on the manner of learning. Constructionism represents a method of pedagogy that concretizes and builds upon many of the ideas of progressive education practiced by John Dewey. Ackermann, (2001) compared the differences between constructivism and constructionism. The latter emphasizes more on learning to learn, through the significance of making things in learning. Technology enables learners to discover learning and knowledge. How learners engage in a conversation with their own or other people's artifacts, and how these conversations facilitate autonomous learning, and ultimately foster the construction of new knowledge. He emphasized the importance of tools, media, and the context in human development. The synthesis of these two perspectives illuminates the process by which individuals make sense of their experiences, progressively optimizing their interactions with the world (Papert, 1991). Kolb believes that experiential learning is a tension and conflict-filled process that occurs in a cycle. Kolb, (2014) stated that the intellectual origins of this theory include the work of Dewey, Lewin, and Piaget. The second reason is to emphasize the central role that experience plays in the learning processes. Kolb's model is mainly based on four stages including concrete experience, reflective observation, abstract conceptualism, and active experimentation. This experiential learning theory differentiates from rationalist and other cognitive theories that emphasize the acquisition, manipulation, and recall of abstract symbols. This theory emphasizes the role of consciousness and subjective experience in the learning loops.

A great number of sociologists, psychologists, and educationalists have provided varied definitions of constructivism because it is a synthesis of ideas from certain learning theories, educational theories, theories of knowledge, scientific theories, and a holistic worldview. Moshman, (1982) distinguished three constructivist paradigms including exogenous constructivism, endogenous constructivism, and dialectical constructivism. Exogenous and endogenous constructivism (rooted in a mechanistic metaphor and an organismic metaphor respectively), the former emphasized the reconstruction of structures performed in the environment, and the latter emphasized the coordination of previous organismic structures and the individual nature of each learner's knowledge construction process. It suggested that the role of the teacher should be to act as a facilitator in providing experiences that are likely to result in challenges to learners' existing models. Dialectical constructivism claims that learners construct views of the self and their world through a dialectical relationship between sensory/perceptual and symbolic/logical information at all times.

The acquisition of knowledge components should adapt in different levels, taking into account learning factors: learners’ prior knowledge, concrete experience, domain knowledge, personalized adaptive learning mechanisms, and learning environments. Experiential learning is a constructivist learning theory that emphasizes ‘learning from examples and by doing’. The learner participates actively in the learning process and acquires knowledge through a continuous cycle of inquiry, reflection, analysis, and synthesis (Brown, 1989). Cognitivist teaching methods aim to assist learners in assimilating new information to existing knowledge, as well as enabling them to make the appropriate modifications to their existing intellectual framework to accommodate that information.

A well-organized learning environment creates learning opportunities for learners, supports and facilitates learning through the techniques of scaffolding, cognitive apprenticeship, tutoring, cooperative learning, and learning communities. Both the external learning environments and the internal cognitive processes of learner are crucial in a constructivist approach. Each interaction between the learner and the learning environment creates knowledge in the context of the entire history of previous interactions. This suggests that knowledge is linked to both the learning environment, the learner's prior experience and current cognitive schemata. Learners are considered to have a very active role and involvement in learning, and they can construct knowledge by interpretation, elaborating, integrating, and synthesizing. Constructivism calls for a learner-centered approach to teaching and learning that supports self-directed, self-regulated, and relatively independent learning, as well as the immediate application of knowledge in new situations. Constructivists emphasize that learner control may not always be effective because learners sometimes need to link new knowledge to what they already know on the basis of the peer collaboration, teacher guidance and a well-structured or organized learning environment. Adaptive interactions and guidance can prevent the learners to become confused and frustrated in their own learning processes.

2.2.5 Social Constructivism

According to Vygotsky & Cole, (1978), the principles of social constructivism emphasizes that meaningful learning occurs since learners engage in social construction. Learning is a continuous movement of cognitive processes from the current level of intelligence to a higher level. The construction of knowledge is based on participation in social activities and understanding human needs, which enables individuals to understand the context and relate themselves to their communities through interaction and cooperation. This movement occurs in the Zone of Proximal Development (ZPD), it is defined as "the distance between the actual level of development determined by independent problem solving and the potential level of development determined by problem-solving under adult guidance or in cooperation with more competent peers" (Vygotsky & Cole, 1978).

Social constructivism examines how humans co-construct an understanding of the world that is based on shared assumptions about reality and specific assumptions about knowledge and learning. The first assumption of social constructivism is that reality does not exist in advance; rather, it is constructed through the activities of human interaction and collaboration. It views knowledge as a human creation, that can be socially and culturally constructed. It assumes that reality was not created prior to the social invention, it is not something that can be discovered by individuals. Members of a society or group jointly create the properties of the world or group (Brown, 1989; Ackerman, 1996; Kukla, 2000). Learners are expected to learn to discover principles, concepts, and facts for themselves and therefore promote their intuitive thinking, logical reasoning and rule induction. Researchers have argued that the social constructivist emphasis on collaboration, transformation, and creativity, learners begin to construct cognitive processes that underpinned by peer collaboration, teamwork, and subsequently generated their own contributions to the body of knowledge. Social constructivist approaches to teaching and learning focus on strategies such as reciprocal questioning, reciprocal instruction, peer collaboration, cognitive apprenticeship, problem-based learning, structured disputed collaborative learning, networked tasks, anchored teaching, and other methods that involve learning with the others. Models of teaching and learning based on a social constructivist perspective generally emphasize the situation learning that need collaboration among learners and social participants (Lave & Wenger, 1991; Gray, 1993; Woolfork, 2010).

As facilitators of social constructivism, instructors first provide scaffolding and support to learners, and then gradually reduce this assistance to allow learners to learn independently. Thus, in a social constructivist classroom, learners are actively involved, the environment is democratic and interaction becomes crucial to learning. Social constructivism focuses on learners-centric instruction. This significant difference in the role of the instructor as a facilitator rather than a teacher, it is that the facilitator needs demonstrating a completely different set of skills instead of providing the responses of predetermined curriculum. The facilitator provides guidance and creates the suitable environment for learners to engage in a continuous interactive dialogue, to draw their answers and conclusions; learning environments should be designed to both support and challenge learners' thinking (Rhodes & Bellamy, 1999). The significant objectives of social constructivism are to promote the learners to be more active in effective thinking, efficient participating, positive initiating and ongoing creation. This goal could be achieved when the instructor has multiple roles, such as advisor, mentor, and coach.

2.2.6 Framework of (Embodied) Cognitive Neuro Adaptive Mechanisms

Frameworks for learning theory have been offered from several disciplines, such as educational psychology (e.g., behaviorism, gestalt, developmental psychology, cognitivism, and constructivism), cognitive neuroscience (cognitive symbiotics, information processing, dual-process, cognitive load, embodied cognition, connectionism, distributed processing, neuroscientific approaches to memory, attention mechanisms, social cognitive neuroscience), biology (e.g., concepts related to brain biological phenomena, and neuro-sustainability, such as neuroplasticity, synaptic density, synaptic plasticity, spike-timing-dependent plasticity (STDP)) and computer science (e.g., one-shot learning, deep neural networks, spiking neural networks) These theoretical foundations include its interplays, which are rarely elucidated with inter-trans disciplinarity, to integrate or unify into (meta) contexts and levels.

Researchers, designers, and practitioners often employ hybrid flexible adaptive learning approaches to address homogeneous or heterogeneous needs of individuals, as well as the challenges of complex environments and real-life projects. Present reviews indicate that leveraging technological solutions to verify appropriate interdisciplinary theoretical and technological models in the contexts could explicitly and implicitly underpin personalized adaptive deep learning effects and training quality. Personalized learning enables learners to discover self-interests, motivation, mindsets, and individual efficiency cognitive styles in problem-solving toward personal development. Intelligent adaptive learning systems tracks and collects customized types of factors and feedbacks, which subsequently provide evidence and insights for (virtual) intelligent tutors to design optimal adaptive and adaptable learning models, to further implement targeted solutions with optimal guidance, prediction, recommendation, intervention, tutoring, scaffolding, and auxiliary.

Connectionism, is a sub-theory of cognitive science, which expects to leverage the effects of artificial neuro learning networks to interpret the phenomenon of human brain, psychological signs, minds, and spirits. Recently, educational sectors and practitioners have gained interest in developing adaptive learning by integration of trans-disciplinary approaches for training learners' routine expertise, adaptive expertise, as well as higher-order thinking, skills and interwoven intelligence. This can be proved and verified by joint research efforts from computer scientists, educational scientists, and cognitive neuroscientists to study and evaluate the design, implementation, applications and impacts of trans-disciplinary approaches, models and complex systems, in fostering physical motor development, human brain abilities, positive psychology, and mental well-being. Brain-inspired intelligence can be employed to interpret the connections, functions of human cognitive neuro networks, to simulate human brain learning activities, memories, and forgetting curves, and neuro networks connection activities. These could be further studied by detecting explicit and implicit human-machine interactive traces and activities; analyzing dynamic intelligent adaptive correlations, cause-effects mechanisms, as well as learning goals and value-added expectancy. All of these are underpinned by adaptive learning engine, personalized cognitive, affective, motivation, metacognitive scaffolding, neuro and bio feedbacks. To amplify performance and mitigate challenges, adaptive learning innovation communities, educational sectors, interdisciplinary practitioners, and learners are dedicated to enhancing systems' adaptivity and increasing learning adaptability. The measurement and evaluation should offer adaptive learning stakeholders the evidence, feedback, as well as insights to interpret the nature, and metaphors of changing learning phenomena, and the variability of adaptive elements, representation. This could be achieved by integrating adaptive technological functions with appropriate contextual and theoretical models. Such integration help in development conceptual frameworks that favor external and internal mechanisms of construction tailored to diverse levels and contexts, and therefore, eventually promoting the quality, viability of learning processes.

Adaptive learning environments employ various well-being and smart technologies for adapting to needs while enhancing engaging adaptive learning experiences. These technologies include ergonomics-enriched robotics, empathetic learning companions, metacognitive scaffolding, embodied learning scenarios such as immersive Virtual Reality (VR) innovation labs, and Mixed-Reality (MR) gamified interactive learning. These adaptive mechanisms may utilize several frameworks such as cognitive style models, and engagement scales to support different aspects and stages of the adaptability during embodied cognitive processes. It aims to achieve several goals: predicting needs, determining optimal time for instruction, identifying proximal zone of cognitive development, optimizing adaptive learning modalities, navigating learning paths, mind mapping, facilitating transferability of higher-order thinking toward interwoven competencies.

2.3 Learning Style

2.3.1 Introduction

This chapter aims to interpret the concepts of learning styles, distinguish the significant features in these models, summary the issues in this field of research, and finally draw the conclusion with the insights for the future research.

Illustration of the suitable adoption of learning strategies has become one of the most important issues in individual learning. Teachers and course designers have confirmed that paying attention to matching learners' strong affinity to a particular learning style would influence the recommendation of learning materials and strategies, and the effectiveness of learning (Felder,1988; Coffield, 2013). In addition, several learning strategies should be integrated to accommodate individual differences and preferences to support learning.

Researchers typically use the terms 'learning style', 'learning strategy', and 'learning preference' interchangeably, the commonly used terminology associated with learning style includes 'information processing style', 'instructional style', 'cognitive style', 'cognitive pattern', 'learning approach', 'personality trait', 'meta-cognitive skill'. Different terminologies have led to the development of many learning models, scales and inventories.

2.3.2 Types of Learning Style

Learning style may involve differentiated cognitive styles, learning strategies, higher-order thinking and skills dimensions, which could be identified and or diagnosed in order to improve the external and internal learning influential factors. These external impactful factors including the design, the provision and the selection of learning environments, instructional strategies, learning sequence activities and contents. It has been justified that the examination of specific effective learning strategies of learner could encourage self-regulated learner to reflect on individual cognitive patterns and to identify self-strengths and weaknesses, which in turn improves the internal factors (e.g., self-awareness, metacognitive abilities and emotional elements) related to personalized learning experience. However, as learning effectiveness not only relies on the efficiency but also on its sustainable impacts. Educators and learners should reflect in what are the goals they expect to achieve and what are the knowledge they should be acquired in short-term and long-term period. Thus, the mismatched learning style should be avoided in order to recommend adaptive and flexible teaching approaches because some dimensions of models and components of learning style might be stable or constantly changed or immeasurable. And these learning theories have been developed to emphasize different factors, variables and types. Thence, the adaptive identification and appropriate syntheses among these models and their key associated relationships with the learning effectiveness and sustainable impacts have not yet been fully explored.

Some theorists have claimed that there are different degrees of stability in learning styles. Curry, (1983) classified learning styles with the criterion in the model of onion based on psychoanalytic assumptions. In Curry's model, each layer represents a different level of stability. Instructional preferences are the least stable ones in the outermost layer as they are conceptualized as flexible and capable of change. It is concerned with various modes of information delivery. Learning is viewed as situated and context-specific (Entwistle et al., 1979; Curry, 2002). The middle layer represents information processing styles, which have more excellent stability over time than instructional preference. They are concerned with the way the brain processes information, which can influence the way learners remember, think, and elaborate on the information. David Kolb, Honey and Mumford and Felder-Silverman model, suggest that learning style is not a completely fixed trait, it is characterized as ‘flexibly stable’. Coffield, (2013) emphasized that valid and reliable assessments should be created for diagnostic and predictive purposes. The innermost (core) layer represents cognitive personality styles/traits, which are believed to be the most stable and even that they are permanent traits that cannot be changed over time. These styles are based on personality traits that have an indirect impact on the way learners interact with the learning environment over a very long period of time (Dunn et al., 1995).

Coffield, (2013) overviewed several learning styles models and classified them into five ‘families of learning styles’ based on quantitative evidence. The styles that are largely constitutionally based include the four sensory modalities such as visual, auditory, kinesthetic, and tactile from Neil Fleming’s VARK model; and the preferences that are constitutionally based on the measurement of environmental, emotional, sociological, physiological, and psychological factors are assumed to be fixed and very difficult to change. For instance, the Dun and Dun model and instruments of learning styles emphasize those variable factors that could impact learning and optimize achievement and academic satisfaction. Below are the crucial interpretations of this term.

• Cognitive structure. Learning styles reflect structural characteristics and deep images of the cognitive system that are embedded in personality construction. The techniques belonging to this family are assumed to be generalized habits of consciousness, thinking, and behavior. It represents the brain, cognitive patterns of ability, and models of style. Gregorc’s mind styles model and style delineator (GSD; 1984) is a self-scoring matrix tool used to identify and measure an individual’s thinking and learning processes. The instrument describes four cognitive styles for perceiving, processing, and ordering information. It is designed to help individuals understand and recognize the ways in which they most efficiently receive and process information. Ring’s Cognitive styles analysis (CSA; 1991) relies on a two-dimensional model of cognitive styles including wholistic-analytic, and verbal -imagery. Cognitive styles are the basics of learning styles. It is a methodology for learners to think, perceived, and even recall information. Allinson and Hayes' cognitive styles index (CSI; 1996) is a self-report psychometric measure of cognitive style that specifically assesses preference-related differences in information processing according to intuition and analysis. Sternberg, (1988) contended that intelligent behavior arised from the effective balance of analytical, creative, and practical abilities. Global level with an abstract and holistic view, and local level with the practical, concrete problems. Intellectual styles comprise a preference for human to use their cognitive abilities to solve problems. Intelligence contains the capability to learn from complicated environments, the cognitive ability to construct schemata, the meta-domain skills to adapt in the environment. Sternberg-Wagner's thinking styles emphasize the ways and preferences of learners in solving problems and developing their styles. The Herrmann Brain Dominance Instrument® (HBDI®) is the global leading thinking styles assessment tool, which measures the four integrated systems that effectively describe clusters of individualized preferences, it identifies learners' mental preferences, and preferred approaches to emotional, analytical, structural, and strategic thinking.

• Stable personality types. Learning styles are a component of relatively stable personality types, which are viewed as embedded characteristics within the personality traits, which are assumed to shape all aspects of an individual's interactions with the environments. These styles and preferences are mostly stable but can be changed. Myers-Briggs Type Indicators (MBTI) empathized that personality preference is measured along four dichotomies: Extraversion/Introversion, Sensing/Intuition, Thinking/Feeling, and Judging/Perceiving. Robert McCrae and Paul Costa's big five traits consist of extraversion, neuroticism, openness, agreeableness, and conscientiousness (Costa & McCrae, 1992).

• 'Flexibly stable' learning preferences. Learning styles are viewed as flexibly stable learning preferences. Although the preferences can change slightly from one situation to another, there is some long-term stability in learning styles. For instance, both Honey and Mumford's Learning Styles Questionnaire (LSQ), and Kolb's Learning Style Inventory (LSI) considered learning can be hybrid flexibly stable cognitive construction processes.

• Learning approaches and metacognition strategies. Moving on from learning styles to a holistic and active view of approaches to learning, strategies, orientations, conceptions of learning, and metacognition includes learning methods and directions. These approaches and strategies need to be adaptable to the learning contexts, therefore, they can be regulated in different learning situations. For instance, Entwistle's Approaches and Study Skills Inventory for STudents (ASSIST), (1991) defined three main learning approaches: deep learning approach, strategic learning approach, and surface apathetic learning approach. Each of these learning approaches is used interchangeably by learners according to the context of their learning. A teacher's behavior and attitude, the course being studied, and other environmental and situational factors form a large part of this context. Vermunt, (1996) identified four different learning styles, meaning-directed, reproduction-directed, application-directed, and undirected, which displayed characteristic patterns of factor loadings across the four components of learning.

2.3.3 Learning Style Models

Given the similarities and differences in many of the terms associated with learning styles, and given the existence of a large number of learning model. A classification of these models can shed light on their key aspects (Coffield, 2013). This chapter summary the core features of classic learning style models. Each model and its components will be discussed in this section.

2.3.3.1 The Dunn and Dunn Model

Dunn and Dunn Learning Style is created in the 1970s, approximately 1975, this inventory measures environmental, emotional, sociological, physiological, and psychological preferences of learners as they affect learning. The learning environment should not be defined only from classroom environment. This environmental space allows the learners feel safe and supported in the pursuit of knowledge, as well as inspired by their surroundings includes seating, light, noise, and color etc. Contemporary learning environment, including face to face, online and hybrid. Learners who study in their preferred learning environment might improve their learning ability and performance. The emotional category is concerned with motivation, persistence and responsibility. These play a part in the complex and highly personal identity of a learning style. The sociological category deals with the types of social interaction, such as the preferences for learning alone, with a peer, in a small group or as part of a team. The psychological category represents how the learner processed and responded to information and ideas: if they are classified into analytic or global, impulsive or reflective. Physiological category concerned how the learners physically engaged in their learning environments with specific preferences of perception or sensory modalities. Dunn and Dunn claimed that these traits might be fixed preferences and may not be changed (Dunn, 1990).

2.3.3.2 The Witkin Model

Witkin et al., (1962) proposed a cognitive-style model concerned with the way learners perceive, structure and recall information. It categorizes learners as field dependent (FD) or field independent (FI), which was the earliest studied area in the study of cognitive styles. The concept of this model is one of variation in cognitive style.

According to Witkin & Goodenough, (1977), FD learners are more socially oriented than FI learners. They rely on social cues, they prefer to interact with others and they seek learning and vocational experiences that put them in contact with human beings. FD learners tend to have a global perspective and may find it difficult to separate minor details from the big picture or the overall viewpoint. FI is a cognitive style in which the individual consistently relies more on internal referents (internal gravitational or sensation cues) than on external referents (environmental cues or visual cues). This type of learners is less reliant on being provided structural materials are more self-motivated. They are analytical and can focus on minor or specific details regardless of the learning environment. However, there are arguments among researchers who emphasized that this model assesses intellectual abilities or cognitive styles rather than learning style (Messick, 1984). Based on earlier work by Marton & Säljö, (1976), Entwistle et al., (1979) developed an instrument for assessing learning style which focuses on the level of processing information and depth of learning. The proposed model centers around four modes of orientation of the learner: meaning; reproduction orientation; achieving orientation; and holistic orientation. Tendencies towards particular combinations of orientations identify individuals as comforting to one of the following learning styles: deep learning style; surface learning style; strategic learning style; and apathetic learning style.

2.3.3.4 The Entwistle Model

The principles of Entwistle's theory emphasizes the importance in placing value on the learner’s individuality, giving learners the freedom to use different approaches in different circumstances, and encouraging them to assess their own approaches and individual objectives.

According to Entwistle’s model, learners’ learning approaches and strategies including surface learning, deep learning and strategic learning. They can be formed on a task-by-task and typically fluctuated over time and mainly influenced by factors such as their orientations to study, types of knowledge and motivation (Entwistle et al., 1979; Entwistle, 2013). Learners who are not intentionally interested in seeking to understand a subject are those take a surface learning approach. They might be those who focus narrowly on the details of the course that are more likely to be assessed. They only pursue the requirements of pedagogical goals, and treat the content as irrelevant knowledge points. In contrast, learners who interact actively and logically with learning content are those adopt deep learning approach. They match ideas to previous knowledge and experiences by looking for patterns and underlying concepts to seek to gain a broad view of the subject. Learners who are aware of the course requirements and the assessment standards of coursework, and combine both deep and surface learning approaches are those take strategic learning approach. They manage the time and effort, evaluate the effectiveness of different ways of studying in order to learn effectively and consistently understand the subject. They identify the right learning conditions and material to achieve remarkable outcomes in terms of course marks. Although many of the subscales of instruments and inventories, such as the Approaches to Studying Inventory, and the Approaches and Study Skills Inventory are developed to measure the learning approaches of learners, there remain the challenges of low reliability, and their test-retest reliability has not been reported (Ramsden & Entwistle, 1981; Coffield, 2004).

2.3.3.5 The Kolb Model

Kolb learning style model, based on experiential learning theory, as an influential figure in this field of research, he emphasizes learning is conceived as a cyclical process, concrete experience, reflective observation, abstract conceptualization and active participations are the four abilities of learners that support effective learning (Kolb, 2014). Concrete experience refers to the way and the ability of an individual observe the results of the action in the context of specific action performed. Reflective observation emphasizes the importance of the ability in reviewing and reflecting upon what has been experienced and done. Abstract conceptualization refers to the ability of learners in the interpretation of observed learning events and understanding the relationships between those events' factors. Active participation emphasizes the ability in the application of acquired knowledge in a new context or situation.

There are four types of learners: converging style learner may construct knowledge with the abstractive and active methods. They perform better in problem-solving tasks, decision making, and generating practical applications from ideas. Accommodating style learner is named as an accommodator who may acquire the knowledge through concrete experience and transform their knowledge into experimentation. They are good at problem-solving activities, but they may be seen as overly proactive and impatient. Diverging style learner may be concrete, reflective, imaginative and human-oriented, they adapt by observation and are able to generate ideas from different perspectives. Assimilator concentrates on abstract conceptualization and reflective observation. They are the learners have strong capabilities to create theoretical and mathematical models and are concerned with logic and abstract concepts rather than interacting with external mechanisms.

Certain learning style inventories including Kolb's learning model as the instrument for identifying learner's type have been proved and also doubted for their reliabilities and validities. For instance, the model that occurred in linear and sequenced steps has been criticized the insufficiency of the integration of social and cultural perspectives. Although Kolb's learning cycle and the elaboration and division of nine types of learners is suitable at analyzing how learning occurs among individuals, it does lack of look at learning that occurs in larger social groups. It may result in false conclusions in understanding and explaining changeable learning phenomenon and experiences. It does not illustrate the fact that empirical (i.e. experiential) thinking based on action has limitations: it does not adequately address the role that non-reflective experience plays in the learning process (Kolb, 2014; Konak et al., 2014).

2.3.3.6 The Honey and Mumford Model

In 1983, British scholars Honey and Mumford model suggested that different learner tend to have a particular learning style and therefore learn best when they understand and discover their own style in the learning processes. It proposed four types of learners: activist, theorist, reflector and pragmatist based on Kolb's model (Mumford & Honey, 1992). Activists are similar to accommodator, they learnt by actively doing and trying something out. They tended to solve problems through brainstorming methods and acted in a direct manner that may lack of sufficient consideration. They enjoyed group activities and tried to place themselves in the center of attention. Theorists such as assimilators and logical thinkers who preferred to involve in the learning processes with models, concepts and facts. They have strong inductive reasoning and modelling skills. They represented as the perfectionists. They preferred to think and solve problems vertically, sequentially and incrementally. Reflectors may be analogous to diverge, they may take an advantage of observation of what other learners do from different perspectives and reflected on them before reaching a conclusion. They may have stronger sense of imagination, understanding and innovation. They may prefer to think twice before acting and may delay decisions-making. Pragmatists is also named as a converger, who may prefer real-world examples and problem solving using standard procedures. They might be more comfortable in doing technical tasks. They may like to try out new ideas, theories and techniques in practical work and practical decisions-making. They should be good at solving problems through hypothesis and deduction, and acquiring knowledge through hands-on experimentations.

The Learning Style Questionnaire (LSQ), a self-report inventory for identifying individuals' learning styles based on the Honey and Mumford model, has been developed in two versions: one contains 80 questions, and the other has 40 questions (Mumford & Honey, 1992; Mumford, 2006).

Although there are positive results regarding the model's internal consistency in the overall implementation in certain cases, there is a lack of evidence and common consensus of supporting its validity especially when it has been questioned as a commercial product or business artifact (Allinson & Hayes, 1990). The LSQ instrument is adopted frequently in management and human resources.

2.3.3.7 The Felder-Silverman Model

In 1988, psychologists Field and Silverman have developed a learning style model that combined the major perspectives, on the basis of the Kolb model (Felder, 1988), the MBTI (McCaulley, 2000), the Honey and Mumford Model (Mumford, 2006), and the Dunn and Dunn model (Dunn, 1990). Felder and Silverman proposed that learning styles could be divided into four dimensions: perception, input, processing and comprehension. Each of these dimensions can be divided into two categories, as follows: information processing (active-reflective), input modality (visual-verbal), information understanding (sequential-global) and information perception (sensory/perceptual-intuitive) (Felder, 1988).

The information processing dimension (active-reflective) is similar to the respective dimension in Kolb's model (D. A. Kolb, 2014). It represents the ways of how learners process the information. Active learners may prefer to learn by trying something out, to acquire knowledge by interacting with peers such as the discussion and explanation. Learners are more likely to understand and assimilate new knowledge when they practice in group presentations and teamwork. Thus, adaptive recommendation strategies should integrate the tasks completion activities in groups. Reflective learners may view and process information in a more reflective way, they might be more inclined to learn and think independently and deeply about the knowledge components before taking actions. Personalized adaptive learning content and strategies need to develop on the basis of prior experience and be empirically relevant. These types of learners may observe and reflect on their own experiences and draw their conclusions only after careful data collection and analysis. They are more inclined to complete tasks independently or with familiar partners.

The input modality dimension (visual-verbal) deals with the preferred input mode and presentation of information. Visual learners may learn well with pictures, graphs and diagrams; visual types might be better at remembering physical objects seen by the eye, e.g., pictures, flowcharts, etc. The recommendation of personalized adaptive learning content and tasks should be visualized or contain more visual material. Verbal learners may grasp spoken and written information quickly. These learners are more sensitive to textual information that they hear or see and have a longer retention time. Personalized and recommended learning content includes both spoken and textual materials. Tasks can be presented in texts or verbally, and summaries of tasks can be diagrammatic.

The information understanding dimension (sequential-global) refers to the preferred way of structuring information. Sequential learners may gain understanding by linear and logical steps and exhibit a strong interest in details, the learners have the logical thinking and the ability to put together a coherent body of knowledge. They tend to solve problems in a step-by-step manner. Recommended personalized learning content should be sequential and progressive. Tasks consist of small units that are logically related to problem solving, and presentation of content can be progressive. Global learners may learn on the basis of large and random leaps through sets of information and have a stronger interest in global and broader levels of knowledge. These types of learners may prefer to jump ahead in thinking to solve complex problems rapidly, complete tasks independently and reorganize everything in new ways, but they might have difficulty in explaining the reasons behind to do so. Thus, presentation and recommendations of learning resources or materials can be random, context-free or concrete.

The information perception dimension (sensory-intuitive) is related to the MBTI (McCaulley, 2000) and also has similarities with the abstract-concrete dimension in Kolb’s model (D. Kolb &

Kolb, 2013). This dimension concerns the most suitable type of information for individual learners. Sensory learners may benefit more from concrete information such as facts and examples. A combination of concrete and abstract learning material can also be provided to learners as appropriate; a concrete-to-abstract sequence of learning material can be provided for sensory learners. Sensory learners should be given concrete learning content. Personalized adaptive learning content should not be detached from reality, using a fact-and process-oriented, concrete approach; tasks should be specific rather than global, including problem solving, experimental exercises and concept memorization. Perceptive learners are characterized by a preference for empirical learning; with preferences for highly cognitive approaches to problem solving; attentive in details, good at memorization but avoiding complexity of work; and the preference for lessons that are relevant to life.

Intuitive learners are characterized by the preferences in learning theories and principles; using innovative approaches to problem solving: they can adapt in complexity and may acquire new knowledge efficiently but they might be careless; they may dislike in memorization and routine calculations. Intuitive learners may perform better with abstract concepts such as theories and mathematical models. The abstract-to-concrete sequence can be more beneficial for these types of learners. Thus, abstract materials should be proposed to them. The personalized recommended learning content needs to be novel, theoretically and methodologically oriented, allowing for the use of abstract concepts and mathematical formulas and avoiding repetitive methods. Tasks are mainly relational and behavioral inquires, and introduction of new concepts should be through abstract concepts instead of factual memorization.

The Felder-Silverman learning style model also identifies teaching styles that correspond to each dimension. It is concerned with instructional methods that supported each component of the model. The Index of Learning Style (ILS) is developed as an instrument for detection of individuals' learning styles according to the model of Felder-Silverman, which contains 44 questions, with each dimension composes 11 questions. ILS is considered as a reliable and validated tool for identifying the learning styles of learners (Felder, 1988; Felder, 2020). Furthermore, the studies have indicated the reliability and the validity through collecting explicit and implicit transparent evidence to verify the adoption effects of each dimension in the model (Zywno & Stewart, 2005).

2.3.4 Design Issues in Didactic Engineering

The conducted critical synthesis of reviews should enable the researchers to identify crucial issues and factors that influence the didactic engineering design, implementation and evaluation of adaptive learning system revolution in higher education institutions (HEIs). The studies reveal four fundamental areas for resolving in the field: the complexity of determining and incorporating adaptive models and intelligent engines into automatic system to optimize resources, sequences and evaluation for lifelong learning; the paucities of hybrid flexible intelligent personalized applications, multimodal adaptive feedbacks and intervention mechanisms, for enhancing self-efficacy learning, metacognition behaviors to facilitate knowledge components and higher-order skills acquisition; the necessity of developing explicit and implicit cognitive neuro tools with reliable learning analytics and responsive (deep) learning and biological technologies to maximize cost-effective learning performance and quality; the opportunities in evaluating the principles and impacts of emerging AI, brain-inspired intelligence, for learning adaptability, underpinned by integrity of trans-disciplinarity, meta human intelligence as well as values regeneration from multi-stakeholders’dedication.

The education sectors have been facing the challenges of design issues such as integration of technological innovation and multidisciplinary intelligence for improving system’ compatibility and learning adaptability with pedagogical goals, effective adoption of models and adaptive learning approaches in didactic engineering. This is especially truth when it comes to develop and combine the models with appropriate theories, intelligent techniques and instructional approaches to meet learning needs in the contexts and specific circumstances. This is mainly due to most of platforms and applications design relying less on modelling and integrating multi-models, interdisciplinary intelligent adaptive mechanisms and transdisciplinary approaches. Moreover, it lacks of verifications of impact evaluation of relevant logical feasibility and sustainability underpinned by rigorous methods.

Although most of adaptive learning research communities are still trying come to terms with the sweeping social and educational implications of intelligent models and adaptive learning technologies, which might be still proliferating, there remain consistent description and understanding of constant changing phenomenon of learning and knowledge transformation in adaptive education systems.

Learning can be individually unique and stable, but it can also be socially dynamic and flexible. In line with the ideological interpretation and uncertain education environments, researchers and scientists have elaborated adaptive learning construction from different stages in various dimensions. These include preparation of learning, guidance, learning support, progression evaluation and feedbacks in macro, meso and micro levels. These adaptive learning scaffolding, feedback loops can be derived and generated from the measurements of explicit and implicit variables, adaptation elements, to further optimize learning parameters, protocols design and adaptive mechanisms development (i.e., pedagogical model, domain knowledge, psychomotor, affective, motivational, cognitive, meta knowledge, neuro mechanisms, ethical, and social-cultural factors). The rules and methods of adaptivity and personalization for improving learning adaptability and effects could be enhanced by the employment of (multimodal) measurement and evaluation of CAMM processes underpinned by traditional methods and advanced technologies.

The construction and impact of an adaptive learning ecosystem

The above chapters aim to present the theoretical backgrounds and explore the design issues in the regard of didactic engineering, and the optimization of learning by appropriate approaches and models. The construction of reliable user' profiles, pedagogical models and adaptive learning mechanisms underpinned by appropriate and logical approaches become the increasingly critical in adaptive learning engineering design. Despite emerging technologies and models have enriched the adaptive features of learning activities to enhance instruction, teaching, and learning through intelligent hypermedia recommendation, tutoring, and feedback systems. Learning systems, which employed single variables, elements, dimension, learning scale or instrument to improve effects has been criticized due to that lack of investigations of logic feasibility and sustainability. For instance, Katsaris & Vidakis, (2021) reviewed the theoretical and the technical backgrounds of adaptive e-learning systems, the study emphasized the impacts of adoption of learning style models. Certain amounts of studies and leading learning researchers and education leaders claimed that significant learning might not be achieved by simply identify learner's characteristics and learning preferences to meet individual development needs. The value the effects of embedding specific methods in learning systems for constructing static or dynamic learning models, sequences, and navigating individual learning needs should be further evaluated. Is it becoming prospective to incorporate authentic dynamic scaffolding, modalities to reframe knowledge structures, refine learner profile, optimize cognitive process, learning transfer and user experience? These daunting design issues are forcing us to seriously reflect the concerns and the challenges that adaptive education ecosystems have faced for long-term.

Currently, there is a lack of substantive and conclusive evidence proved the adoption of static or dynamic teaching, learning and evaluation can make a significant contribution to maximize performance and learner achievement (Felder, 2020). The investigations of the effective implementation measures might be also limited in short-term period, narrow-range projects, small-scale and samples of learners.

Despite high-quality studies of learning style scales and robust experimental evaluations considering all the confounding factors and functions have been conducted, and certain positive influences in learning have been emphasized, there remain the unresolved concerns and the unverified logic feasibility and effects in developing learning activities and systems by employing learning preferences to identify and accommodate learning needs. The traditional tools and methods of measuring or evaluating user' preferred learning modalities is often criticized. This is due to the education sector' limited time, resources, and capabilities in assessing constantly changed learning style and modifying adaptive instruction accordingly (Akbulut & Cardak, 2012; Truong, 2016). Indeed, diverse adaptive factors, variables (e.g., learners' knowledge, motivation, emotion, metacognition control and abilities) should have been taken into consideration in the context of human-centered adaptive learning. Therefore, the effects of these measurements still differ widely in terms of validity, reliability especially when complex model are embedded into simple adaptive learning system to verify design needs, and to develop individual learning activities.

Effective learning mechanisms might be ensured when educational practitioners employ intelligent techniques to evaluate learners' traits, states of cognition, emotion, motivation, metacognition, and provide them adaptive instruction, learning activities, and scaffolding to facilitate knowledge acquisition and reinforce skills transfer (Nye et al., 2018; Dai et al., 2023). Intelligent features-enriched adaptive learning environments, which adapt instructional styles and sequences in learning needs, should have the capabilities in mediating learning, improving performance and maximizing efficiency. Meaningful learning requires underlying design principles with adaptive learning science, as well as effective verifications of technological features and functionalities, and it may also depend on differentiated evaluation of hybrid flexible adaptive approaches to ensure the reliability and trustworthiness.

2.3.5 Impacts of Adaptive Learning Technologies

In the recent decades, intelligent adaptive, predictive and generative AI techniques have been widely adopted as powerful advanced didactic tools in identifying instructional needs, detecting learners' status, predicting learning performance, prescribing learning sequences, reasoning learning difficulties, recommending learning solutions and activities. Emerging AI such as Gen agents, multimodal optimization systems, embodied pedagogical (conversational) agents, synthetic companions, empathetic metacognitive tutor, avatars have been widely employed to track and analyze invisibly learners' learning trajectories, interactive behaviors, emotional responses, learning strategies, learning gains and risks. Deep learning technologies enable simulations of user' physiological model, cognitive model, metacognitive model, brain and neurological factors to provide different levels as well as types of task-specific feedbacks, neuro feedbacks and bio feedbacks. These advanced learning analytics, biometrics, and adaptive assessments may employ multimodal optimization to construct personalized adaptive learning experience.

Notwithstanding, validity and reliability continue to rely on the revolutions of Artificial Intelligence (AI) and Human Intelligence (HI) for adaptive guidance, learning modalities, support, interventions, recommendations, effective model construction and sustainable impacts evaluation. Machine learning and brain-inspired intelligence as technical solutions in enhancing the decisions-making abilities of intelligent tutoring and adaptive learning systems, which try to deal with the issues of personalized intelligent learning, feedback loop construction, as well as effective application according to the evidence of quantified methods. In contrast, human intelligence makes efforts to improve learning performance and quality through feasible qualified evaluation approaches to ensure learning adaptability and sustainability.

Emerging adaptive technological and feedback models have been widely adopted in learning management systems, adaptive learning platforms, personalized learning applications. However, adaptive learning stakeholders still face the challenges in role-playing for fostering significant learning for individual and social development, this is mainly due to the ill-defined definitions of corresponding adaptive learning theoretical models and mechanisms constrictions in the contexts, levels and duration. In fact, adaptive learning stakeholders are still struggling in designing specific techniques for the cyclic adaptation in situational learning, and interpreting significant impacts and subsequent feasible measures for valuable learning experience.

2.3.5.1 Implications of Instructional Practices and Adaptive Learning

Current adaptive teaching methods and learning approaches stand by macro-educational system, content adjustments, communities buildings, meso-knowledge goals construction, learning management models development, and micro-levels of individual learning adaptation that origin from the technological revolution, evidences of learning trajectories, human-decision making and effective strategic evaluation etc., The roles building of multi-stakeholders from cross-sectors become dramatically significant, since they may begin to engage in adaptive learning system design, project implementation and development.

The sub-chapters firstly focus on emphasizing significant involvement of adaptive didactic engineering in developing intelligent adaptive learning systems geared to educational objectives, transformation of educators, and training of learner adaptive capabilities in 21st century. Didactic sequences, predictive learning and recommendation modalities that may influence instructional practices and adaptive learning outcomes. Indeed, teacher-led adaptive instruction, pedagogy, and evaluation systems do not necessarily lead to high quality construction of precise learning mechanisms for promoting individual adaptive learning.

Despite this, meaningful learning could be processed and ensured in the conditions when learners acquire distinctive interests, positive motivation, resilient self-regulation behaviors, heighted collaborative regulation capabilities, and socially-shared regulated skills in asynchronous and synchronous learning preparation processes in the context of hybrid flexible adaptive learning space and working environments. Learning preferences, cognitive style models, engagement scales might be simply resources and measures that assist adaptive learning designers, instructional practitioners in developing types of assessment mechanisms, exploring individual preferred learning modalities, personal traits, interactive behaviors, and academic performance. Indeed, self-efficacy learners are expected to equip metacognitive knowledge components and meta-control abilities, thus, learners are encouraged to co-design or self-select optimal learning modalities that suits in their corresponding intrinsic motivation, knowledge levels, learning goals, personal and social value construction for the development in hybrid flexible learning environments.

In contemporary hybrid flexible learning contexts, embodied adaptive and smart learning have been increasingly adopted in synchronized learning settings to provide both inclusive and personalized learning for heterogenous learners. Presently, the integration of micro, meso and macro levels of metaverse, generative AI applications, deep learning models, brain-inspired intelligent adaptive learning mechanisms and smart technologies into new paradigm of adaptive education system are becoming demanding. The design, deployment, and implementation should bring ubiquitous learning and interactive opportunities, enable diversified systems and multi-learning stakeholders to collaborate, and create personalized content, generate adaptable strategies, organize learning progression, optimize task performance, demonstrate learning outcomes as well as academic achievements. Thus, hyper intelligent adaptive generative deep learning techniques are encouraged to be incorporated in learning management systems (LMS), which could be possibly constructed underpinned by advanced technologies such as human cognitive digital twins, digital twin-brain, neuro adaptive mechanisms, well-being learning systems for fostering user-centered solutions, they are also expected to stimulate cognitive learning processes, emotional intelligence, metacognition flexibility, neuro sustainability and social intelligence in asynchronous learning settings (Khalil, 2024; Srivastava et al., 2024)

2.3.5.2 Implications for Knowledge Transfer

Adaptive learning engineering often dedicate in designing and implementing effective curriculum contents, pedagogical activities, didactic approaches, knowledge map construction, cognitive levels tracking, learning optimization, performance measurement and impact assessments. The impacts of these measures need to be evaluated under the standard of education feasibility and viability in transforming knowledge models to meet sustainable development goals. The training of 21st century skills (i.e., higher-order cognitive functions, efficient operational execution, problem-solving, critical thinking, logical reasoning, meta-control and meta cognitive abilities), has become the goal of precision learning and quality education. The training objectives of these higher-order skills might not be realized simply by teaching explicit factual, conceptual knowledge or developing basic literacy competencies. Adaptive learning systems are expected to investigate differentiated learning, inclusive approaches and efficient targeted solutions for mastering not only multidisciplinary academic knowledge, but also interdisciplinary intelligence, meta domain-general knowledge, individual-specific skills, and interwoven intelligence.

Adaptive learning communities barely emphasize the importance in investigation of an optimization system with multiple-channels, integrative models and cost-effective solutions according to automatically selected criteria and adaptive approaches for accommodating the constant changing needs of heterogeneous learners' upskilling and reskilling training in hybrid agile circumstances. Indeed, there remain paucities to analyze different use and impacts of learning mechanisms in the composition of higher level of success in adaptive learning, and intelligent training models.

Personalized adaptive learning support, feedback and solutions in facilitating meta-domain general and individual-specific knowledge acquisition processes have become promising techniques and methods for increasing learning success and teaching adaptability. Adaptive hypermedia and instruction technologies often use engagement scales, learning style models, personalized preferred approaches to customize adaptive content, provide optimal tutoring and affective experience. As emerging user-centered generative artificial and human-brain-inspired intelligent technologies are possibly incorporated into complex learning management systems, these adaptive learning and cognitive scaffolding technologies must be aligned with applied learning science, theories of connectivism, cognitive neuroscience, metacognition, affection, for improving learners' capacities in controlling cognitive neuro functions, motivation regulation, emotional management, metacognition adjustments, as well as adaptive socially-shared learning efficacy to promote cognitive resilience and knowledge transitions.

A key of personalized learning method is to develop interactive explicit offline and implicit online (meta) cognitive mechanisms to interpret significant adaptive learning through exploration of learner' proximal cognitive development zone and learning needs in order to recommend optimal resources, avoid cognitive load, and promote (meta) cognitive flexibility. Learner' proximal zone of cognition and metacognitive skills become particularly important factors of meta learning and adaptive system development that foster knowledge transformation within the circumstances. The integration of metacognitive scaffolding, auxiliary models and adaptive neuro and biofeedback mechanisms into systems has been expecting to optimize learning scenarios for individual learning as well as different types of skills transfer (Tosti et al., 2024; McNamee, 2024; Adityo, 2024).

The construction and impact of an adaptive learning ecosystem

Trans-disciplinary approach for research endeavor should be crucial in developing reliable and responsive adaptive learning environments. The significance of creating guidance framework is to provide comprehensible interpretation in not only, adaptive education, pedagogical objectives, technological features developed by educational sectors. It should integrate with the objectives of learner's neurocognitive development for personalized adaptive learning processes, as well as human emotional interaction needs based on socially shared learning in the context of global digital transformation considering political economic, cultural-historical perspectives. The indicators, criteria, variables for learning effectiveness or sustainability are extremely significant to stakeholders as these factors can often be improved beyond the provision of learning content, training, activities and methods. One of design concerns in the regard of developing adaptive learning models relates in resolving the issue of system adaptivity, and also the issues of users' academic buoyancy, resilience, learning adaptability. Brevity, adaptive learning designers are decoding know-why (concepts) and know-how (procedures) for constructing effective learning mechanisms that facilitate (meta) cognitive processes and enhance the efficiency of knowledge components acquisition as well as learning experience transfer. Furthermore, stakeholders are facing the challenges in evaluating of learning impacts maximization and mitigation, on the basis of incorporating both adaptive features and functionalities to enrich the design, the implementation of diverse learning activities, as well as human-like adaptable mechanisms, this therefore, should help in significantly facilitate learners' higher-order (meta) cognitive knowledge, skills development, innovation construction, human well-being and value transitions.

2.4 MAXIMIZING LEARNING IMPACTS AND MINIMIZING TRANSFORMATIVE CHALLENGES

Although, large-scale studies proved that digital techniques have enriched adaptive features in improving overall learning performance and academic achievements. The impacts of intelligent technological features haven not yet been influential comprehensively by appropriate selection of theoretical models, and interpretation of adaptive learning design principles in the contexts.

It has been agreed upon those learning impacts might due to the results of: specifically adaptive technologies enriched design features (e.g., simulations, intelligent tutoring, adaptive feedbacks, promoting, exemplifying, scaffolding, remedies, hints), implemented in learning environments. The specific approaches and efforts of multi-learning stakeholders, and how they make use of these technologies. Recent trend indicated the generative deep AI models and applications may revolute the education system at scale and lead to great potential challenges. Brain-inspired intelligent, well-being systems fostering sustainable neuro-cognitive adaptive learning mechanisms construction and simulations have proved the effectiveness in optimizing learning impacts, and minimizing transformative challenges, which therefore become a priority in developing personalized adaptive learning for the transitions in society 5.0.

Intelligent adaptive learning encompasses a broad variety of approaches, sophisticated technologies and tools, which can be embraced in the context of education 5.0. Indeed, investigations and studies often focus on the mere presence and development of systems with advanced intelligent technologies, and interpreting general learning effects by certain benefits of implementing particular types of methods. Nevertheless, studies demonstrate that logic construction, evaluation and combination of trustful adaptive models can generate positive impacts on the optimization of (meta) cognitive construction processes as well as the transformation of knowledge types. As a result, reliable adaptive education system development for risk management, policies-making and strategies regulations should be encouraged to amplify learning impacts and mitigate transformative potentials of emerging AI in learning.

2.4.1 Intelligent Adaptive Mechanisms Facilitate Cognitive Processes

Present literature reviews show insufficient illustrations and arguments in logically feasible construction and impacts behind the proliferation of newly artificial intelligent models and technologies. And how learner-centric learning mechanisms construction could be enhanced by intelligent techniques, appropriate learning theories, and principles in the specific contextual models: to fuse the body of ontology and epistemology; to further diversify the systems of knowledge; to facilitate the processes of (meta) cognition; and to improve the human experience of learning.

Neuro-cognitive pedagogy, adaptive learning science underpinned by emerging AI are playing significant roles in dramatically improve construction of adaptive models, optimization of learning contents, modalities, and sequences of learning tasks. Certain conducted studies proved adaptive deep learning has influenced the identification of learners' intentions, preferences, cultivation of personal traits, training of (meta) cognitive skills; it has also improved diagnose assessment of (meta) cognitive processes, meta-control, operational functions, knowledge mastery in loop of disequilibrium, assimilation, accommodation and equilibration, together underpinned by flexible adaptive learning systems or automated communication tools. These may bring benefits mainly by improving differentiated instructions, learning recommendations from intelligent textbooks, and adaptive feedbacks for individuals. They also have important implications in customizing (personalized) adaptive pedagogical scenarios, curriculum contents, course adjustments according to various adaptive elements.

Automatic solutions can overcome the limitations of statically determined methods, Natural Language Processing (NLP) and transformer models enable the optimization of learning paths, and the reinforcement of personalized learning approaches. For instance, Essa et al., (2023) indicated that Artificial Intelligence (AI) can be used in developing dynamic and personalized learning in adaptive learning systems by utilizing Machine Learning (ML) algorithms to tackle the challenge of personalizing e-learning by mapping learners' behavioral attributes to a particular learning style automatically; accurately define learners' profiles that reflects personal characteristics; and dynamically optimize individual learning process with natural language processing and text speech (Waladi et al., 2023).

2.4.1.1 Integration of Learning Model and Effective Evaluation

Intelligent adaptive generative systems that integrated adaptive learning models, should enable the capacities in providing customized content, information or personalized pedagogical scenarios and activities to adapt in specific learning needs, improving instructional effectiveness, learning outcomes, knowledge retention, as well as user attention, confidence, satisfaction (Benfarha et al., 2024). Chaimae et al., (2024) proposed an intelligent and dynamic model for fostering adaptive learning construction, which took into account entire learning process, casual loop described from diagnostic assessment to knowledge assimilation. Their approach utilized the model of Kolb and combined algorithms such as K-means classification to group learners' similar characteristics. To enhance the accuracy of model and improve the performance, investigation also incorporated neural networks to automatically predict learning preferences, and used Decision Tree (DT) to propose adaptive pedagogical content to learner. Lamya et al., (2024); Anoir et al., (2023) designed personalized pedagogical scenarios and learning approaches, which adapted in individual and collective needs. The study provided personalized learning activities according to learner' s profile, which is based on learning instrument from Kolb model, with the aim to develop a learning system that can establish a link between personalization and adaptation. It applied the Kolb model for determining learners' profiles, preferences and needs throughout their (hidden) behavior patterns and subtle learning processes in different activities.

Kaiss et al., (2023) developed a personalized recommendation method that achieved the adaptation of learning objects according to learner's learning style based on Felder-Silverman learning style model. The technological solutions that employed artificial intelligence (AI) technologies such as machine learning (ML) and natural language processing (NLP), focused mainly on employing a chatbot named Learning Partner Bot as automated communication tool to mimic the conversations by detecting user's intentions. The type of technology is also expected to be integrated into Moodle platform. WAAM & HKS, (2024) used machine learning to detect learners' attributed combinations within Felder Silverman Learning Style (FSLSM): global-moderate, visual-strong, perceptual-moderate, and reflective-strong. The study assisted instructors to understand which components of learning content should be improved during course design.

Nevertheless, the effects of intelligent technologies and models integration enriched different types of adaptive instructions, hypermedia, tutoring, and learning environments, also depending on specific design goals, implementation approaches, multidisciplinary collaboration, effective performance evaluation and personalized adaptation (Benfarha et al., 2024; Ikram et al., 2024; Chelliq et al., 2023). Although, advanced intelligent adaptive learning technologies, have been identified by the capacities in simulating learners' characteristics and developing their abilities, such as aptness, positive psychology, emotional expressions as well as social intelligence such as sympathy and empathy. However, intelligent technologies and learning models may or may not theoretically or practically underpin promising logical construction of sustained adaptive mechanisms and (meta) cognitive tools that facilitate efficiently user' external and internal meta psychology, cognitive flexibility, knowledge acquisition, meta levels of intelligence and social value transfer.

2.4.1.2 Developing Effective Learning Mechanisms Adapted to Circumstances

Although, the employment of certain artificial intelligent techniques such as predictive, adaptive and generative models, proved the values in co-creating dynamic interactive learning, especially in facilitating the construction of heuristic, socratic, personalized exploratory and experiential learning activities. There remains insufficient evidences and impacts evaluation about how specific technologies underpin meaningfully (meta) cognitive processes, optimize effectively adaptive learning paths, sequences, scaffolds dramatically higher-order cognitive functions, complex skills acquisition, as well as development, in line with appropriate theoretical or contextual models (Zaoui Seghroucheni & Chekour,2023; Chaimae et al., 2024; Lamya et al., 2024; Ayyoub & Al-Kadi, 2024).

Thus, research efforts, which align with why adaptable learning mechanisms (i.e., internal cognitive mechanisms) may stimulate (meta) cognitive activities and learning opportunities; when intelligent adaptive technologies and tools should be effectively employed to enhance these learning processes; what are underlying principles beyond these external and internal mechanisms; and to which specific human-centric intelligently enabled design features and relevant instructional practices are key interests of implementation. The evaluation of adaptive learning environments is therefore underpinned by adaptive design features and principles in heterogeneous contexts and specific circumstances. It is worthwhile to identify and reflect on that positive effects on learners' significant learning and knowledge transformation may be rooted in the interplay and the mediation between external scenarios, and internal (meta) cognitive psychological construction, as well as neuro adaptive mechanisms. For instance, simulations within an adaptive personalized learning environment may guide learners to develop (meta) cognitive tools to reason the physical phenomenon and practical works. Meanwhile, integrating adaptive (meta) cognitive scaffolding inside versatile, multimodal reinforcement learning agents, emotional system or intelligent meta cognitive tutor may help learner to dynamically improve self-regulated learning, adaptive collaboration, and socially shared-learning capabilities(Colombo et al., 2021; White & du Boulay, 2024).

Consequently, we recommend to verify which appropriate construction principles of feasible intelligent learning models, how adaptive features of reliable technologies on influencing learning performance, what responsive assessments in specific cause-effects of significant learning stimulative and integration methods mediated by both external learning activities and internal cognitive mechanisms, and their variations in the contexts (i.e., within knowledge assimilation, accommodation and adaptive transformation processes).

2.5 Illustrating A Common Reference Framework

This chapter aims to explain a comprehensive didactic framework, with key interest in guiding theoretical reflection and recommending practical implementation in different stages and contexts of learning. It is oriented in interpreting relevant situations of adaptive and adaptable learning mechanisms construction and impacts in hybrid flexible, automatic recommendation, intelligent interactive, social collaborative learning spaces/environments. These are mainly done by the synthesis of reviews and the reflection of a series of knowledge components, cognitive basis, learning principles, instructional design features, guidelines of adaptive contexts. For that, we draw on models which generally capture the structure and dynamics of learning in adaptive and adaptable contexts. And we explained how constructed learning mechanisms may foster (meta) cognitive construction and adaptive learning transfer. Therefore, this study goal is threefold, firstly, we integrate multiple adaptive elements in reference to the aforementioned theories and principles in order to resolve the concern in terms of changing phenomenon and perceptions of learning. Secondly, with the respect of these theoretical foundations and principles, we illustrate how the presence of information communication technologies reinforce learning interactions among participants and accommodate knowledge transformation. Finally, illustrating the learning mechanisms on the basis of system adaptivity and learning adaptability to stimulate meta(cognitive) processes and significant learning activities. First, one of the bodies of this architecture, mainly refer to the topper layers of presentation within this framework, we intend to explain how the external adaptive environments could be designed within feasible didactic principles so as to stimulate learning and knowledge acquisition, and elaborate how dynamic procedural structures can be well constructed to underpin adaptive learning (tutoring and recommendation) with technologies. Furthermore, the objective is to explore how observable knowledge representations, instructional features and assessment strategies influence (internal) cognitive processes and knowledge acquisition. Second, the other bodies of this architecture, mainly refer to the bottom layers of this framework, we reframe the internal personalized learning processes within adaptive (meta)cognitive activities to generate learning and knowledge transformation. In reference to these aforementioned adaptive components, the learners actively learn and regulate cognitive and behavioral activities to adapt to their working memory rhythms. These dynamic cognitive construction activities play roles in selecting, filtering, organizing external learning resources, prior cognitive structure, domain-specific knowledge and experience, and combining them into the long-term memory and cognitive schemata. Since every learner might have heterogeneous (meta)cognitive strategies and learning patterns. We further argue that developing appropriate approaches to capture/track external users’ interactions, internal cognitive processes, generate personalized feedbacks and scaffolds should be helpful to improve adaptive learning and communication mechanisms. In these adaptive mechanisms, learning analytics, adaptive evaluation, biometrics, deep learning could be employed to diagnose, sequence, recommend, and regulate. The purposes are to provide real-time adaptive resources, tools, learning opportunities, assessments and feedbacks during their interactions with environments-since these cognitive processes and dynamic adaptation loops are vary substantially among learners. An ideal approach is introduced by adoption of adaptivity-learning-adaptability mechanisms to assimilate and accommodate learning. ALA mechanisms are not to distinguish between explicitly external learning supports and internal (meta)cognitive processes. A critical focus point of these mechanisms focuses on the interplay interpretation about how they potentially employed the technologies reinforced learning on one hand (e.g., instructional settings) -that have functions for behavioral change and cognitive psychology activation. These interplays and impacts led by precision learning and quality education in stimulating ways and levels of learning engagement and progress. And actual learning performance and impacts on the other hand (i.e., the internal effort of individual learner experience in the processing of information, transforming learning and constructing knowledge).

Since the dimensions of these adaptive elements and mechanisms appear highly relevant for theoretically defining adaptive learning and empirically investigating in designing artificial intelligent technologies mediated adaptive learning in hybrid flexible contexts, the introduction of the comprehensive framework (D-C-ALA) - a didactic (DKTI) framework dedicated in developing the mediation of adaptive learning and evaluating the impacts in the contexts that incorporates both the core values of the D, C and ALA. - i.e., core values from trans-disciplinary research (Fig.3). For an analogous framework that composited designs of didactics, teaching principles and instructional activities to facilitate multiple phases of learning and initiate knowledge transformation (See the "Acquisition of knowledge in adaptive environments with feasible didactic design" section). For an analogous framework that constructs and characterizes personalized learning, cognitive psychology and behavioral processes to stimulate self-regulated learning patterns (see the "Construction of (meta) cognition in adaptable environments with schemata" section). Since learning are both external behaviors and internal cognitive processes. External symbolic activity, (e.g., explicitly observable interactions, visibly interpretable prescriptions and adjustable solutions). Internal cognitive psychology perspective, (latent and implicit, e.g., adaptation, regulation). (Meta) cognitive processes, as well as behavior construction mediated by adaptive learning mechanisms lead to the continuous transmission and evolution of learning during the interactions, which result in knowledge transformation, higher-order skills development.

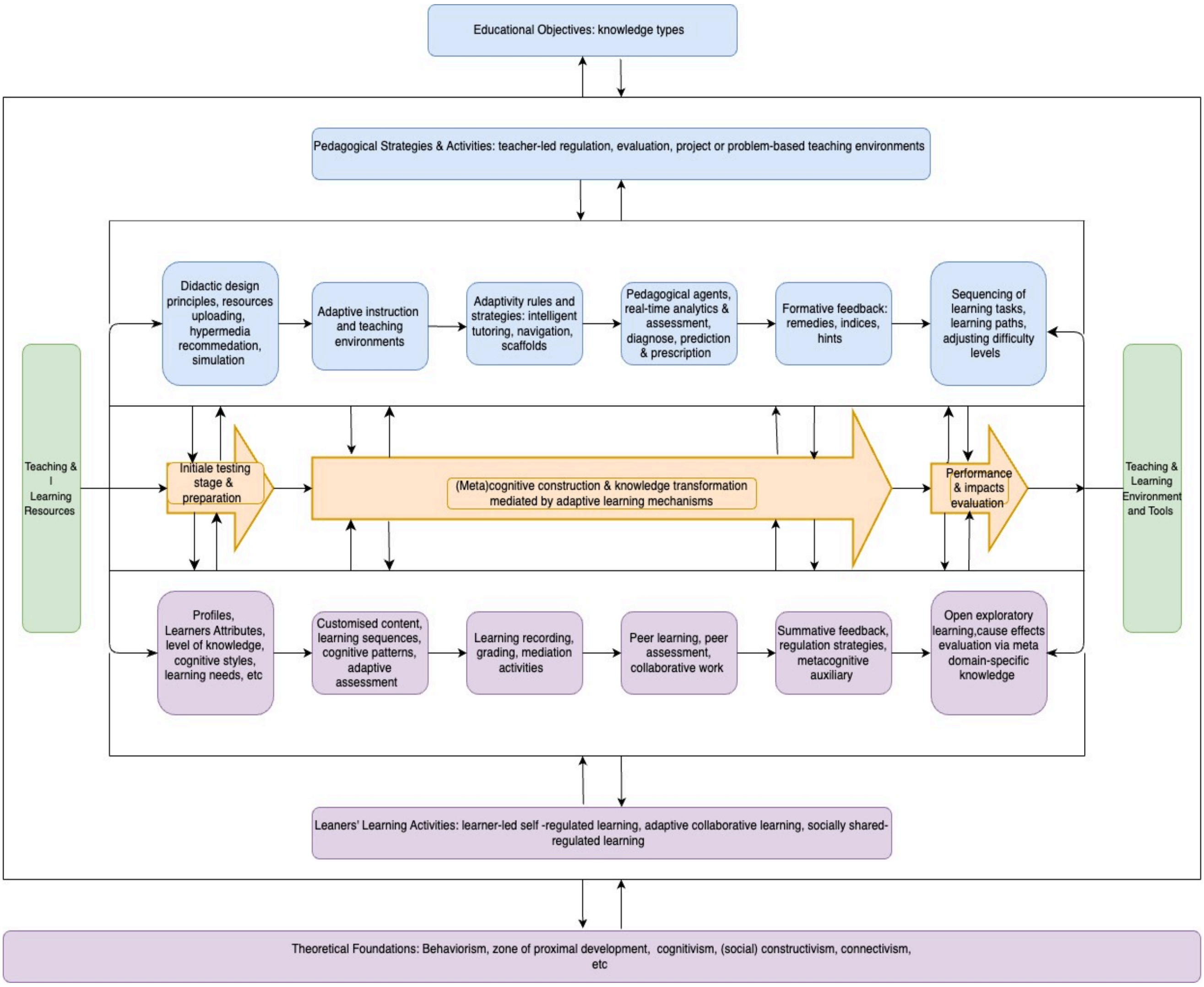

Figure 3. A common reference framework

By combining the different theories to adapt in the construction of hypermedia, instruction, teaching and learning requirements, the framework serves to derive the principles of adaptive didactics for optimization of design, implement embodied adaptive learning experience and situational feedback loops. The cognitive framework for facilitation - adaptable learning capabilities connectively (meta)cognitive processes to generate learning, and the learning mechanisms for evaluation-linking learners' performance with behaviors and (meta) cognitive psychology. These trans-disciplinaries researches underpinned by sciences such as neuro-pedagogy, meta cognitive science, intelligent adaptive technologies generated and reinforced deep learning: we suggest how they can be integrated to theoretically ground the design of various mechanisms for hybrid flexible contexts, why they are appropriate to frame correlational or causal research endeavors, and how they can guide the evaluation of learning activities in intelligent techniques reinforced learning experience based on appropriate operationalizations of human-machine collaboration. We exemplify the utility of this comprehensive framework by framing the most recent investigation and studies on the knowledge integration and adaptive technologies impacts with regard to this framework.

2.5.1 Learning as Individual Context, Subject and Content-Specific (Meta) Cognitive Processes to Generate Knowledge

Acquiring knowledge components in different learning settings

With the respect of aforementioned learning theories and principles, it is feasible to interpretate that learning are the human natural active (meta) cognitive processes for the adaptive interaction with the changing environments. The aim is to build and regulate external and internal learning mechanisms, which can promote the acquisition of knowledge components or the construction of cognitive schemata. The knowledge components define the cognitive structure, knowledge levels and types. Cognitive processes and activities specify the prior knowledge or experience that can be activated during learning, and the evolving knowledge including misconceptions in knowledge points and adjustable strategies that develops throughout the (meta) cognitive process. Since the knowledge components, types and levels of difficulty available at any point in time influence the learning activities, a subject content-specific analysis of these factors is a fundamental basis of understanding learning mechanisms construction, and thus derived design principles that implemented in these learning environments to maximize the effects of knowledge acquisition. These knowledge components acquisition is evolving and updating constantly through the multiple ways, which connected to elements and outcomes from perceptions and interplay between learners and learning mechanisms. The knowledge components include intelligence can be developed through the efforts of continuous cognitive structure construction and learning experience improvement. To explain better these actions and processes, the theory of Piaget involves the interpretation of concepts: disequilibrium, assimilation, accommodation and equilibration. Assimilation refers to how learners absorb, select filter and organize the information from external environments, combine them with domain-general experience or domain-specific knowledge facts, and stimulate new learning activities and skill development with their cognitive schemata; accommodation refers to when new environment or circumstance occurs, prior experience or current cognitive schemata might not able to assimilate new information or problem, learners need to modify or create schemata to adapt to new environment or circumstance. Knowledge components include intelligence and wisdom rely on continuous disequilibrium, assimilation, accommodation and equilibration, which can balance gradually the complexity of adaptation within the circumstances. Disequilibrium, equilibration respectively refer to the non-adaptive and adaptive learning processes and learners' responses when absorb new cognitive schemata and acquire knowledge. Consequently, the bottom layers of this framework, which aims at interpretating adaptive learning in the acquisition of knowledge components should explicate on the one hand, internal, implicit and unobservable activities and processes of learning transfer, cognitive schemata construction and knowledge transformation. And on the other hand, external, explicit and observable subject or content -specific analysis and evidences of interactions, performance, achievements.

Both above mentioned processes of cognitive construction and learning behaviors can be traced by adaptive models and technologies. The external learning activities, contents, supports and interventions with the aim of realizing learning effects could be prescribed for activating dynamic cognitive schemata. The theory of Piaget defines learning and cognitive schemata constructive activities as the objectives of learners to acquire, assimilate, accommodate, integrate knowledge components through a series of related contextual tasks and actions taken in learning experience.

The learning performance and quality can be described, diagnosed, predicted, inferred by internal cognitive tools and optimal metacognitive strategies. For instance, since the cognitive structure; the knowledge components, the levels and the preferences of learners are varied due to the differences in their prior experience, personal traits and attributes. These factors dedicated in motivating and stimulating the internal learning activities and influencing the design of adaptive hypermedia, instruction, tutoring, mentoring, learning and recommendation activities. Thus, learners profiling and cognitive modelling are important adaptive elements to facilitate the construction of adaptive learning environments, and to understand the effective learning mechanisms so as to achieve the knowledge construction or skills acquisition as well as learning transformation. For instance, Vygotsky & Cole, (1978) defined zone of proximal development as the focus point or benchmark to stimulate, optimize and adapt in personalized learning and experience, which specified the prior knowledge that can be activated during learning adaptation. It reinforced learning with the evolving cognitive processes of higher-order cognitive functions and skills acquisition based on the adaptation of individual proximal zone of cognitive development.

The construction and impact of an adaptive learning ecosystem

In general, personalized adaptive learning as individual (meta) cognitive construction and regulation processes to acquire knowledge components. These often involve in mediating adaptive learning mechanisms and accumulating implicit evidences to realize the holistic adaptation and feedback loop throughout the dynamic testing, measurement and evaluation. Context, subject and content specific cognitive processes should allow the testing of significant learning throughout adaptive theories and strategies to match with learners' domain-general experience and domain-specific knowledge or (meta) cognitive models toward personalized learning domain. Thus, these links in how adaptive environments or systems mediate internal learning mechanisms by considering relevant variables such as learner types (e.g., attributes, levels of knowledge, cognitive styles and learning needs), adaptive reinforced learning principles (e.g., behaviorism, cognitivism, (social) constructivism, connectivism), adaptive deep learning strategies (e.g., learner-led self-regulated learning, adaptive collaborative learning and socially shared-regulated learning). And on the other perspective, to explain how (meta) cognitive construction and knowledge transformation can be mediated by explicit adaptive learning mechanisms which employed relevant methods, techniques, tools such as adaptive elements (e.g., customized contents, learning sequences, cognitive patterns, adaptive assessments), adaptive learning analytics and evaluation techniques (e.g., learning recoding, grading, mediation activities), adaptive interactive methods (e.g., peer learning, peer assessment, collaborative work), adaptive learning supports (e.g., adaptive summative feedbacks, regulation strategies, meta-level intervention and metacognition auxiliary), and open exploratory learning as well as cause effects evaluation via the balance between prior domain-general knowledge, experience and meta levels of domain-specific knowledge.

2.5.2 Learning Activities When Learning with Adaptive Learning Mechanisms and (Meta) Cognitive Tools

Significant learning and cognitive schemata construction mediated by adaptive and (adaptable) mechanisms

Yet, constructing the internal individual (meta) cognitive construction and external learning activities based on appropriate didactic design principles and adaptive features might not guarantee effective learning transfer and knowledge transformation for each learner. Therefore, adaptive learning mechanisms that mediated by both external explicit learning interactions and internal actual cognitive processes seek to integrate the comprehensive aspects and holistic viewpoints to facilitate significant learning. These mechanisms commonly focus on making decisions on the measures-end analysis of what, who, when, where, why, how the construction of intelligent tutoring and adaptive learning in the hybrid agile context. In its usual impacts, the main evaluation involves in pedagogical attraction (in terms of improving learning engagement), teaching to be effective (in terms of improving overall performance and quality) and learning to be significant (in terms of developing adaptive strategies and improving results). These underpin that learning is considered to be individual, generative, reflective, active, socialized and collaborative processes-in line with connectivism and theories of self-efficacy, particularly in monitoring (meta)cognitive activities and developing relevant strategies.

However, for better combine these design principles and adaptive models into the construction, of effectively adaptive internal and external cognitive tools and learning activities, the conceptualization of learning mechanisms focuses on both implicit and explicit individual cognitive schemata, and collaborative working patterns and to be content and context-specific. For that, adaptive learning mechanisms describes the integrative learning effects in both digitally, psychologically, mentally enriched design features of adaptive environments, which can be characterized via specifically designed elements or approaches enriched adaptive instructional functions and learning features. Such cognitive schemata construction tools and adaptive mechanisms, including the activities that learners do or do not engage in when interacting with adaptive learning settings, the theoretical predictors of learning outcomes, and the evaluation techniques or evidences of performance.

Moreover, this comprehensive framework differentiates between the external, behavior, observable, explicit side, and the internal, psychology cognitive side. The external side of learning activity encompasses specific interactions that occur when learners work with the implemented digitally enriched instructional features and adaptive environments; the internal side of a learning activity encompasses of implicit cognitive processes or non-observable mental efforts initiating and accompanying the adaptive actions and interactions with external environments. However, for disentangling each learner's utilization of learning opportunities provided by digital tools, the conceptualization of adaptive learning mechanisms and learning phenomenon, needs to focus on describing learning opportunities in personalized adaptive flexible educational settings, which are characterized via specially design principles (e.g., individual-specific, as well as context-subject-content specific).

Among others, such meso-level of adaptable learning mechanisms constructed by knowledge communities to improve learning performance and quality, user experience, learners' higher-order thinking, cognitive functions, adaptive expertise, that is relevant for initiating and stimulating learning opportunities, regulating and mediating adaptive learning strategies, can be demonstrated by the following elements and approaches for promoting cognitive processes and higher-order thinking:

- Conducting experiments: Hands on, virtual or simulated experiments for learning, training and testing. In the learning stage, learners adapt in the specific schemata through the processes of perceptual learning and cognitive construction. In the training stage, learners acquire knowledge for problem-solving. And in the testing phase, learners are examined about knowledge mastery and levels of skills.

- Law of effect in practices: Strengthen or reinforcement is the basis of this learning mechanism, which indicate the cognitive construction processes and stimulative methods in response to trials and errors.
- Analogy: In the context of similar domains, the learning phenomenon can be interpreted as analogy: when there are similarities in knowledge components, or problems or learning tasks that need to be resolved during the phases of training or testing, in comparison with learning stage.
- Learning transfer: In the transformation of knowledge components in different domains, learning phenomenon can be interpreted as transfer learning when learners are able to generalize knowledge and skills to resolve the problems in different contexts or fields where learner can find common knowledge components with individual prior knowledge or experience.
- Abstraction: Contextualized complex knowledge (unit), or simplified task to a more generalizable level.
- Refinement: Improvement of precision and quality of knowledge by making it more specific, accurate or discriminating.
- Compounding or optimization: Involving in enhancing problem-solving efficiency through optimization of learning paths.
- Revision or tunning: Fundamental restructuring or improving inspiration methods or rules of domain-knowledge to adapt in the processes of problem-solving on the basis of contextual needs of learning circumstances. For instance, domain- knowledge, or learning

tasks can be contextualized into generalized level or specific level according to learners' prior domain-specific knowledge or experience.

- Chunking: Chunking mechanisms contain the functions of compounding and tunning.
- Mean-ends analysis: Learners acquire knowledge from analysis of the examples with problems-solving steps. Learners discover the differences between former and current steps, as these show them cues, and enable them to think: how to take further actions or measures. Therefore, obtain new schemata production for the practices.
- Proceduralization: Construct domain-specific knowledge construction or schemata production in the processes of problem-solving. This cognitive activity takes the intellectual manipulation, as the procedure of utilization and combination of factual, conceptual and procedural knowledge to encode information or problems, and to characterize them into memory.
- Creating examples: Expansion of the range of variation, diversifying the differentiated examples, exploration of the boundaries.
- Meta-cognitive activities: Self-monitoring learning behaviors, metacognitive strategies in self-regulated or efficacy learning processes. For instance, exploration of learning objects to activate relevant prior knowledge, self-explain new-to-learn content to oneself. Elucidation of the raised inquires, evaluation and self-reflection of knowledge mastery, self-position, and self-organize learning plans to foster deeper learning.

Cognitive processes, metacognitive strategies, which are specifically assumed to explain how these learning activities result in the acquisition of knowledge components. Furthermore, how these schemata and (meta) cognitive tools select, organize, and integrate prior experience and new-to-learn content to construct new knowledge, and develop higher order skills, which may be effectively integrated into the already existing cognitive structure of the long-term memory. This new cognitive structure enables learners to apply the acquired schemata, as well as the skills in new situations or circumstances. For brevity, these cognitive processes involve particularly in the external interactive behavior side and the internal cognitive side of learning activities. To be more specific, adaptive learning mechanisms contribute to the development of intelligent features enriched cognitive systems to facilitate precision learning opportunities. Internally, adaptable learning mechanisms dedicate to the interpretation of cognitive construction processes, that result in connection of new to-learn content with prior experience, thereby generate cognitive structure, and develop new schemata beyond the given contexts.

Although such cognitive processes and activities relating to concrete domain-general experience, domain-specific knowledge, context-specific model, which can be all the interests for developing learning environments. Theoretical and empirical studies often lack of context-specific analysis. There is a paucity of efficient learning mechanisms conceptualization investigations that assist in understanding and explaining why certain learning activities may make specific types of learners succeed or more efficient while certain fail.

Yet, we consider the construction and the elucidation of these adaptive learning mechanisms necessary to answer these types of questions of why and how both leaning and cognitive dimensions work well, and what make learning to be significant, as well as what enable learners to be succeed. In the context of this comprehensive framework, such adaptive and adaptable learning mechanisms functions, serve as the bridge between behavioral interactions with external digital environments, and the internal needs, (meta)cognitive processes that lead to user experience of knowledge acquisition, as well as adaptive transformation. More particularly, this framework develops a cognitive map and decision-making guideline, which aims to illustrate how learners' interactions, engagement in adaptive activities, performance cause-effected by internal (meta) cognitive processes, as well as external mechanisms as necessity for significant learning.

2.5.3 Digital Instructions and External Mechanisms in Stimulating Significant Learning

In line with educational objectives in the acquisition of different types of knowledge, pedagogical strategies, such as teacher-led regulation, problem-based tutoring, and evaluation criteria can be served as the guideline to didactic design principles and instructional features. When referring to two of them, a critical reflection and design concern is that external learning environments are mere external cognitive tools to deliver new-to-learn content and sustain resources, but may not maximize learning adaptability, due to the limitations and challenges in cause-effects evaluation. Certainly, specific features enriched intelligent personalized learning approaches may accommodate individuals to accomplish learning tasks and to activate their cognitive construction, stimulate information and knowledge transformation activities by different measures. Such didactic activities frame the patterns of resources uploading, hypermedia recommendation, simulations. Such adaptive instruction and teaching environments frame strategies and rules of adaptivity. The functions of these adaptive technologies, containing intelligent tutoring, navigation and scaffolds. Pedagogical agents can be deployed by dialog-based intelligent tutoring, conversational learning companion, chat-boat and synthetic agents, which are able to build real-time learning analytics and assessment so as to diagnose, predict and prescribe further steps of learning. These multimodal analytics and adaptive models drive real-time, formative feedbacks, remedies, indices, hints. The results are able to generate adaptive learning regulation strategies, sequencing of learning tasks/paths, and adjusting difficulty levels of both curriculums, as well as practical works.

In the context of this comprehensive framework, the features of instruction, tutoring, evaluation, learning recommendation are understood as following design principles and instructional features: instructional events, which have the potential to stimulate active learning activities due to them being subject of affordances and constraints; to foster adaptive learning activities by reducing cognitive load; and to increase generative processing when compared to non-digitally enriched educational settings. This is in line with the cognitive theories of multimedia learning and of reinforcement deep learning. The interpretation of learning mechanisms with corresponded principles, designed features that are based on the adaptive parameters such as educational contexts, cognitive needs/objectives, and learning impacts. We consider, among others, the following intelligent techniques and adaptive features enriched adaptive instructional practices as the essential.

Adaptive Hypermedia

- Dynamic adaptive hypermedia as a technological solution that adapts the content and presentation in the requirements of learners and the ways they prefer to absorb and assimilate information. Thus, it may foster reinforced adaptive learning and adjustment activities for mastering conceptual knowledge. Adaptive hypermedia system integrates the adaptive models, leverages the functions, adaptation strategies to optimize user experience (Benfarha & Lamarti, 2024). It uses domain model to organize the resources or content into learning objects, and knowledge concepts; the model optimizes the subject structure and constructs their relationships to provide the relevant materials and activities that align with learner's profiles. It adapts in level of difficulty, and sequence of learning activities by leveraging the evaluation results of outcomes, performance, progress, preferences, and cognitive strategies (Ikram et al., 2024).

- Adaptive hypermedia technology can recommend hybrid flexible adaptive resources, as well as providing customized social learning experience that align with learner's dynamic behavior and cognitive level (Wongwatkit & Panjaburee, 2023). For instance, when if the group of homogeneous learners are in strong affinity of auditory and tactile learning activities, they may be interested in engaging in socially activated, gamified learning, the software may initiate the exploration learning activities by recommending multimedia resources and embodied collaborative conversation simulations. Adaptive hypermedia application may emphasize cognitive scaffolding techniques, such as abstraction, context-free, domain-specific schemata to accommodate sequential or reflective learners to acquire factual concepts or procedural knowledge.
- Within the functional perspectives of integration instructional model between hypermedia and recommender systems, duplex adaptation mechanism may promote flexibly deep learning activities, as it dynamically updates the format of presentation, instructional strategies, adaptive learning sequences, recommendation and feedbacks through multi-channel interaction information retrieval, user profiling, multi-modal dynamic modelling (Machado et al., 2021; Wongwatkit & Panjaburee, 2023; Purificato et al., 2024). For example, the system may help learners to find the resources most fit their needs, or offering corrective promotes, task-specific remedies, problem-solving hints, or adaptive feedback according to learner's multi-behavior modelling, concept understanding, knowledge types mastery (Iftikhar et al., 2024).
- Adaptive hypermedia that characterized with personalized adaptive approach could prevent learners' cognitive load from exploring hyperlinks, stimulate significant self-regulation and interactive learning transfer activities, it therefore, improve knowledge acquisition, assimilation, transformation, performance and engagement. It may recommend

additional learning opportunities for individuals to be actively involved in self-reflection, meaningfully acquire individual higher-order skills, ultimately maximize their lifelong learning effects and inclusive values.

Adaptive Instruction

- Adaptive instruction enriched systems are commonly involved in providing wide range of adaptive tools, supporting varying degrees of support. They are often evaluated by their benefits on both instructor-led training and learner-oriented learning contexts within hybrid flexible environments. Adaptive instruction may stimulate fine tuning activities, as it integrates the models and leverages their functions to optimize self-regulated learning and adaptive collaborative learning experience and maximize these learning impacts. This approach may support a variety of learning resources, formats, materials, activities in the contexts to support pedagogical innovation for addressing issue of attraction by meeting learners' abilities and needs. It uses domains-specific knowledge model to organize instructional resources or content into specific objects, and knowledge points; domain-specific knowledge model to optimize knowledge structure; focusing on a combination method to provide the assessment and activities that align with learner's performance. These may involve the quizzes, exercises, practical tasks, assignments, lectures, tutorials and collaborative works.
- Adaptive instruction adapts in dynamic needs of learning, levels of progress by leveraging the evaluation results of instructional practices, strategies, performance, and behaviors (S. Wang et al., 2023). Within the functional perspectives of the instructional model, it may promote flexible tutoring and deep learning activities, as it dynamically adjusts the forms, intensity, and levels of instructions, feedback mechanisms and scaffolding techniques,

relating to the information acquired from learning management system, domain knowledge model and learner model. For example, the system may offer immediate or delayed, corrective promotes, task-specific remedies, problem-solving hints, adaptive levels of feedbacks according to learning goals, types, levels or proficiency of knowledge.

- Adaptive learning mechanism that developed with adaptive instruction may stimulate refinement activities of cognitive structure and revision activities of meta-cognitive strategies because it breaks down the objectives into different sub-objectives or sub-tasks. Learners may self-solve problems through a deep understanding and memorizing of conceptual knowledge with personal preferred modalities such as abstraction or sequenced activities, and or they may learn by metacognitive self-regulated and reflective learning methods.
- Learners could receive instructions with different types of resources, knowledge and adaptive levels of difficulty, which aligned with their prior experience, ongoing interactive behaviors and individual domain-specific knowledge (Sanal Kumar & Thandeeswaran, 2024). Adaptive instruction may also stimulate analogy, fine-tuning, generalization, context-free, context-specific and discrimination activities to acquire aspired learning outcomes. As learners have different levels of knowledge, these strategies may facilitate the efficiency in solving problems or working on tasks in the same or different domain.
- Adaptive instruction may employ hyperlink visualization, intelligent textbooks, intelligent tutoring, interactive chat boats, embodied conversational pedagogical agents, adaptive-machine learning, and socially collaborative learning programs, to facilitate motivation, apprehending, stimulating information processing, knowledge acquisition, retention, recall, assimilation, accommodation, and transfer learning. It may stimulate learners who prefer to learn with active, auditory, visual methods that underpinned by both learner-

control resources and system-controlled progresses environments, which enabled them to shift from teacher-led instruction to self-regulated learning process with metacognitive activities that may lead to improved learning outcomes (Lennon, J. M. 2023).

Intelligent Tutoring

- Intelligent tutoring systems are typically implemented in structured learning and formal training environments. As it involves the varying types of support from personalized adaptive tutors or agents, these systems are often evaluated by their impacts on providing interactive tutorials and personalized real-time guidance in problem-solving processes or practical exercises, tasks and assignments under the accurate monitoring and prediction of learning performance for formulating specific type of tutoring approaches (Almarzuki et al., 2024; Bhatnagar & Agrawal, 2024). It may activate learning by examples and doing, stimulate adaptive activities through one-on-one or small-group information tutoring feedback, step-by-step meta cognitive navigation, and adaptive content (Zhong & Zhan, 2024). It may also facilitate means-ends analysis and stimulate meta cognitive activities through enhancement of procedural knowledge. Since the similarities and differences between steps can compose learning cues to realize the efficient manipulation. And each changing operation or adaptive adjustment enable learners to encode cognitive schemata. ITS may recommend tutorials and scaffolding according to learners' proximal development zone of cognition, enabling them to regulate, respond to stimulative activities. For instance, ITS may offer information tutoring feedback services including task-specific tutoring, remedies, problem-solving hints, or personalized feedback based on trying and errors.

- An adaptive model or mechanism in ITS may stimulate refinement activities and revision activities, as it constructs adaptive learning paths and provides personalized navigation to meet the specific needs or preferences. Learners may learn to solve problems through adaptive intelligent tutoring processes. It may also stimulate self- exploration teaching and learning activities, develop personalized strategies to achieve training objectives. By combining learner's dynamic learning trajectories and chaining cognitive states, ITS may effectively forecast and appropriately design instructional materials, sequence adaptive learning activities, adapt in learning paths, provide personalized feedback and promotes according to learner's abilities and cognitive status (Hawari & Oktavia, 2024). Adaptive learning mechanisms in ITS may promote learner' cognitive development, acquisition of problem-solving skills, and enhance their knowledge mastery. It may provide specific benefits for learners to be actively involved in practicing, regulating, reflecting, constructing and evaluating, ultimately improved both tutoring effects and learning performance.

Dialogue-Based ITS

- Dialogue-based intelligent tutoring systems, conversational applications, embodied pedagogical agents, such as learning companion, Chat GPT, are often employed in personalized learning software, and integrated in learning management system (Scarlatos, 2024). The multi-agents, chat-boats may be embedded in the user-interface to encourage interactive discussion simulations. They are evaluated by increasing effects with these personalized learning activities and feedbacks. It may facilitate cognitive construction of knowledge acquisition and development of meta cognitive skills. It may stimulate deeper learning transfer activities.

- DB-ITS may stimulate inquiry learning, self-exploration, self-regulation, self-adaptive activities. As it may dynamically articulate various types of inquiries and posing based on the detection of learning needs. It may provide formative feedback, construct learning trajectories, create interactive simulations of learning scenarios. It may employ a synthetic agent to play multiple roles to foster learning transfer activities. It may also integrate independent learning agents to conduct particular tasks and provide different learning supports. Learners may be able to pose the raised questions, to select the learning or testing content, regulate the strategies and adapt in personalized content that provided by these tools. However, learning effects are varied in terms of individual knowledge levels, cognitive abilities, and meta-cognitive strategies.

Intelligent Tutoring Systems + ITS+

- Intelligent tutoring systems + are often employed in broader scope of adaptive learning techniques, including virtual reality (VR), augmented reality (AR), mixed reality (MR), digital twins (DTs), cloud computing, block chains, and generative artificial intelligent (AI) models to implement in smart campuses. Adaptive intelligent tutoring and user interface systems may foster explorative learning, interactive and simulative activities. Synthetic neural networks and deep learning techniques may be used in tracking and collecting the multiple dimension datasets to provide the inclusive, as well as personalized learning mechanisms.

Exploratory Learning

- Exploratory learning approach are often employed in open-ended hybrid flexible learning environments to stimulate social constructive activities. The learning mechanisms may foster adaptive interaction and collaboration activities, such as peer learning, peer evaluation, peer collaboration or gamified learning.

Adaptive Learning Environments/Ecosystem

- Adaptive learning environments/ecosystems often employ above mentioned adaptive elements to stimulate optimal learning activities, create adaptive curriculum, didactic sequences, and adjust management services (Alam, 2023b). It may employ both automatic and traditional methods to collect datasets, build protocols, adaptive parameters and indicators based on the requirements of learning stakeholders. Learning Analytics (LA) and Educational Data Mining (EDM) are able to provide dynamic feedback loops that mainly generate decisions about when to adopt adaptive hypermedia, adaptive instruction, intelligent tutoring, personalized mentoring, scaffolding, interventions, and recommendation. Adaptive posing enables learners to acquire external consultative information when they are not sure of the requirements of a task or the objectives of problems. Enabling learners to make self-posing that allows them to obtain explorative or inquiry information when they are not sure of cognitive states or levels of problems.

Adaptive (Meta) Neuro Cognitive Scaffolding

- Adaptive meta cognitive scaffolding systems are employed in supporting the development of meta cognitive behaviors and skills. These scaffolding techniques are often developed and evaluated by their impacts on improving learner's learning adaptability. It may create various adaptable learning mechanisms to support positive emotions and foster productive learning activities. It may stimulate deeper learning by managing cognitive loads. It may develop meta cognition monitoring abilities and skills to improve learning gains, outcomes and performance. For instance, the improvement of correction rates, computational thinking skills, proficiency of problems-solving. It may stimulate meta cognitive strategies, as well as self-regulated learning behaviors, such as self-plan, self-evaluation, self-reflection, self-efficacy.

Multiple positive impacts of education system can be realized by offering more scaffolding to improve learning performance; providing corrective feedbacks, task-specific hints, prompts, remedies for the measurements and assessments of knowledge mastery, levels of difficulties in the tasks; recommending reinforced learning and transfer approaches, analogy, and hypothesis for evaluation of learning effects, outcomes and quality. Certainly, these features can be designed to suit in traditional classroom settings and non-traditional learning environments as well, following the above agreed principles of adaptive learning mechanism design. The implementation of hybrid agile adaptive learning environments may remain promising and challenging since the affordances and provision of trans-disciplinary-based adaptive learning come into play.

2.6 CONCLUSION - RESEARCH ON HYBRID AGILE ADAPTIVE LEARNING UTILIZING THE COMPREHENSIVE DIDACTIC FRAMEWORK

As a synthesis of above-mentioned principles within the models, the comprehensive didactic framework may serve as a holistic guideline, to instruct external learning and internal cognitive mechanisms construction for learners to acquire knowledge components, as well as providing educational practitioners the insights and decisions-making solutions. More specifically, structuring research endeavors within the framework, in the development of learning mechanisms aligns design principles and instructional practices with (1) theoretical foundations of internal individual learning and strategies used during cognitive processes of (2) a specific knowledge component, context or objective. It focuses on concerns on (2) the assumed underlying external learning behaviors and cognitive activities which the (4) intelligent design features enriched adaptive educational settings and learning activities should enhance and stimulate. Therefore, it may help adaptive learning environments constructors, researchers and educators to collect the evidences, and establishing a bridge to link internal cognition developmental needs to the improvement of their on-task performance or behavior, which allows for testing and evaluating cause-effects of why specific features of instructional resources, cognitive tools and learning mechanisms can benefit in learning. However, the research needs to align strategies and efforts on the further development and more evaluation of framework studies.

CHAPTER 3: REFLECTION ON THE CONSTRUCTION AND IMPACT OF AN ADAPTIVE LEARNING ECOSYSTEM

Emerging technologies are enabling adaptive learning systems to develop. This specific system consists of several models, including a learner model, domain knowledge model, instructional model, learning analytics model, and adaptive engine model. This paper reviewed multiple studies and highlighted the importance of refining each model in the context of creating a conceptual framework. We also proposed a metacognitive auxiliary model and an adaptive assessment model. The objective is to advance research into logical transitions in the internal structure of an adaptive learning ecosystem through the interpretation of different approaches, technologies, and solutions that facilitate the decision-making processes.

3.1 The Objectives of Adaptive Learning In Society 5.0 (Introduction)

Although the COVID-19 pandemic has caused unprecedented disruption of the learning environment (Bozkurt et al., 2022; Pokhrel & Chhetri, 2021; Policy et al., 2021), it has simultaneously accelerated a number of innovative initiatives based on various aspects of Industry 4.0 technologies. Education 4.0, which aims to transform contemporary education by opening innovative models and dynamics of action around new standards, mobilizes a broad coalition of relevant stakeholders to drive systemic change (Rahim, 2021). In parallel, the Education 5.0 paradigm, in the context of Industry and Society 5.0, emphasizes effective, personalized, adaptive, and quality-oriented learning (Darmaji et al., 2019; Aprilisa, 2020). This may mean a gradual shift towards values-based and human-centered digital social innovations in teaching and learning (Carayannis & Morawska-Jancelewicz, 2022). Thus, in the post-COVID-19 pandemic era, higher education must rethink how to combine and integrate the benefits of blended training to enable the development of adaptive learning ecosystems.

Adaptive learning refers to the methodologies, techniques, and tools to improve the learning mechanism through learning analytics, optimizing learning, adjusting content types or levels, customizing learning-sequence activities, and providing adaptive feedback and remedial solutions according to specific needs (Capuano & Caballé, 2020; Kabudi et al., 2021). The transformation of adaptive instruction models to adaptive learning models is critical in enhancing the adaptive capabilities of both the systems and the learners. This involves redefining adaptive learning and the roles and behavioral approaches of stakeholders. It enhances performance and quality at the level of hybrid training in higher education addressed to the industry of the future. The present research shows that the interpretation, construction, and impact of adaptive learning remain questionable due to varying contexts. There are two groups of characteristics that are central to adaptive learning: First, diversity and adaptivity, since training instructions, learning content, learning paths, and learning strategies adapted for specific learners may or may not be appropriate for others, given that in many situations many users learn via tutoring systems or pedagogical agents where teachers take on various roles such as mentor or consultant when on-demand assistance and intervention are required. Second, adaptability and personalization, since the learning objectives, learning-sequence activities, and cognitive strategies recommended for groups of similar learners may or may not be appropriate for some of them, given that in many situations the decision-making abilities of many users may not be up to prioritizing personal learning objectives among these various recommendations, where systems such as adaptive educational hypermedia are designed to be flexible and user-compatible (Sakkinah et al., 2022).

This synthesis of the literature reviews the theoretical concepts and examines a possible future of adaptive learning, especially when emerging educational artificial intelligence is applied to enhancing learners' adaptive capabilities in future learning ecosystems. The theoretical models of adaptive learning and its relevant terms are defined. Different approaches to adaptive learning design are classified for reflecting on the sustainable implications of developing hybrid, flexible and logically feasible implementation mechanisms. The generic reference models, modelling techniques, and analytics for implementing classical adaptive learning systems are also studied. These models and techniques are designed to improve the design of adaptive teaching and to optimize learning path recommendations. Meanwhile, this study incorporates two models into the standard framework for implementing a commonly defined adaptive learning ecosystem, which may enhance personalized and adaptive learning.

Through this synthesis, our goal is to identify criteria for measuring the impact of adaptive learning systems. To that end, we look at different indicators, including performance, logic, feasibility, and sustainability. We provide a common reference for evaluating all of these initiatives according to objectively comparable criteria, despite their potentially different natures. Finally, we make recommendations for solving the problems identified, which may prove useful for future work on the effectiveness of adaptive learning.

3.2 Illustrating a Common Reference Framework (Background and Motivation)

To begin a meaningful illustration of adaptive learning theory and practice, we need to conceptualize an ideal framework based on the contextual background to help us rethink what innovative, feasible, and sustainable solutions are and to guide our understanding of them. This framework focuses on investigating adaptive learning as a multi-dimensional, multi-level exploration of the phenomena, problems, methods, techniques, and patterns of contemporary learning. The insights provided by different parties can be particularly helpful and influential, especially when the implementation of adaptive learning is not only the responsibility of teachers. This is because adaptive learning benefits tremendously from having a multi-disciplinary approach: the different perspectives lead to improved performance, logical feasibility, and sustainability. When considered from a pedagogical engineering perspective, developing the systems for adaptive learning implementation is therefore a joint action by pedagogical engineers, system designers, etc., (Zargane et al., 2023). From the epistemological perspective, it is knowledge innovation engineering, which is the open innovation of domain knowledge experts, including teachers and learners, in developing adaptive learning processes to facilitate knowledge transfer and value sharing for a sustainable society (Berding et al., 2021). And from the didactic perspective, it is how didactic engineers and researchers work with teachers to design logical and feasible instruction, teaching and learning processes, analysis, and assessment programs based on a knowledge of learning theories and methods that are dynamically adapted to learning needs and goals (Grugeon-Allys et al., 2022). The learning perspective illustrates the process by which learners construct learning trajectories, and develop cognitive strategies and metacognitive abilities in technology-reinforced, self-regulated, adaptive, collaborative, and socially regulated learning environments (Park et al., 2023; Lhafra & Abdoun, 2023; Sobocinski et al., 2022). The feedback and records generated should be helpful for teachers and learning analysts to guide the design of adaptive interventions. In general, we are looking for an anchor based on all these insights to identify a reassuring mental anchor (map) that can serve as a benchmark to help us reorient ourselves with a more innovative and sustainable adaptive learning ecosystem.

Adaptive learning systems can be interpreted differently due to the heterogeneity of projects and the visions of experts across disciplines. Although intelligent tutoring systems, adaptive learning systems, and recommender systems have been identified as having and varying degrees of capability (Kabudi et al., 2021), they are all categorized as adaptive intelligent learning or tutoring system due to the similarity of adaptation indicators and elements (Erümit & Çetin, 2020).

Moreover, the versatility and agility of a system are not necessarily the only criteria for evaluating whether it is adaptable and adaptive. Adaptive learning transformation requires multiple reviews based on different approaches. The interdisciplinary approach is designed to allow a more holistic interpretation of the phenomenon of adaptive learning engineering transformation. The transdisciplinary approaches allow the combining of theoretical models, logical approaches, and practical considerations in the development of adaptive learning mechanisms. These efforts enable the creation of a framework dedicated to improving the construction of an adaptive learning ecosystem, as well as reflections on the sustainable implications.

3.3 Method

Critical Interpretive Synthesis (CSI) was developed for multi-disciplinary and multi-method evidence, which involved an iterative approach to refining the question and searching and selecting content (Edwards & Kaimal, 2016). In this review, we used CSI to explain, argue, and evaluate multiple studies on the theoretical models of adaptive learning design, systems, and technologies. This methodology allowed for exploration of the relevant concepts, and enrichment of the perspectives by critically combining the different literature and iteratively analyzing them using thematic synthesis.

A total of 52 scientific publications that met the eligibility criteria were assessed.

- The key phrases, such as adaptive learning, personalized learning system, adaptive learning ecosystem, open learner model, didactic of adaptive learning, and evaluation, are included in the article titles.
- The objectives, adaptive indicators, modelling methods, techniques, and types of systems are well-defined and explained.
- The system is designed for promoting self-regulated learning, adaptive co-regulated learning, and socially shared learning purposes.

3.4 Theoretical Framework

3.4.1 Adaptive Learning

The theoretical underpinnings of adaptive learning are complex and multifaceted. The interpretation of adaptive learning can be very heterogeneous when it is concerned with learning from theories of psychology and cognition. The term "adaptive" refers to the capability of learners to constantly adapt to distinct situations, to produce physically and mentally distinctive behaviors. Adaptive learning is a synchronous and asynchronous process of knowledge transformation in which learners facilitate problem-solving and knowledge construction. With the rising popularity of STEAM education, contemporary adaptive learning theory encourages learners to discover learning from examples and to acquire knowledge and skills in a problem-solving manner through practical works. Adaptive learning approaches based on Gestalt psychology and multiple intelligence learning theories emphasize the performance of learners' psychological and situated cognitive behaviors in generating insight learning, productive thinking, and transferring learning (Anisimova et al., 2020; Alam & Mohanty, 2022). Meanwhile, adaptive learning approaches that are underpinned by specific or a category of learning theories (e.g., connectivism, zone of proximal development, cognitive load, and cognitive flexibility), emphasize in how learners develop autonomous learning with self-regulation, adaptive- interaction, and self-efficacy strategies. From the principles of educational technology, adaptive learning that based on the information processing theory, emphasizes the interaction between the consciousness of cognition and the ontology of learning for knowledge transmission. It integrates the characteristics of adaptivity and adaptability to provide pedagogical scaffolding, feedback techniques and tools. Simultaneously, adaptive learning incorporates static and dynamic learning analytics techniques (e.g., descriptive analytics, predictive analytics, diagnostic analytics, inferential analytics, prescriptive analytics, cognitive as well as metacognitive analytics) to facilitate the development of intelligence in the knowledge level and the metacognitive abilities of heterogeneous learners. The learners' and systems' adaptive learning capabilities are fundamental in the construction of a sustainable learning experience ecosystem. As in many situations, different types of users have distinct objectives and changing requirements in terms of improving the performance and quality of domain or specific knowledge.

3.4.2 Learning Ecosystem

The effectiveness of self-regulated, co-regulated, socially shared strategies for regulating the development of metacognitive systems for adaptive learning has facilitated developments in learning technologies and pedagogical applications from different levels and perspectives. This includes individual adaptive learning, adaptive collaborative learning, and adaptive symbiotic learning ecosystem.

The recent reviews suggest that there are benefits to integrating technological advancement with adaptive learning in a hybrid environment based on human-centric perspectives. Digital Twin (DT) is a promising technique comprising a multidisciplinary, multi-probabilistic simulation, a multi-dimensional digital mapping system for adaptive learning in the context of Society 5.0. The latter term refers to a super-smart social welfare system that is dedicated to addressing human needs (Carayannis & Morawska-Jancelewicz, 2022). The advantages of DT are that it relies on living models: it can replicate or simulate all the elements, processes, dynamics, and firmware of physical systems and entities as digital counterparts (Fuller et al., 2020; Mihai et al., 2022). It could be used to monitor, intelligently perceive, diagnose, predict, analyze, and optimize digital learner models and propose remediation strategies and solutions. The emerging technology of Cyber-Physical-Social-System (CPSS) aims to functionally integrate human beings at the social, cognitive, and physical levels into a Cognitive-Cyber-Physical System (CCPS). The incorporation of new technologies such as human digital twins (HDT) and cognitive digital twins (CDT) may enhance adaptive learning (Zhang et al., 2020).

AI learning platforms and embodied applications such as smart campuses, intelligent tutoring systems, virtual and immersive classrooms, and social robots are becoming increasingly prevalent in digital transformation. The cost-effective, flexible and reliable cloud-computing infrastructure enables the creation of an e-learning ecosystem. With the advent of technologies, it becomes realistic to implement learning management systems and social collaborative mechanisms at universities. This new ecosystem allows the collection of high-dimensional data, increases the sampling of dataset variables with measurable criteria, enables the expansion of adaptive indicators, as well as of the scope of adaptive targets, approaches, and technologies. These initiatives are expected to improve the compatibility and usability of adaptive learning ecosystems. This may help to improve performance, achieve a sustainable socio-economic impact, and bring a perception of added value and attractiveness to the adaptive learning ecosystem (i.e., higher education institution).

3.5 Summary of Adaptive Learning Design Approaches

The historical review demonstrated that the design of the classic didactic triangle model integrated various indicators with attempts to implement adaptive instruction. Thus, this synthesis of the literature elaborated on the dimensions of the didactic polyhedron of adaptive teaching and learning based on the adaptation from macro, micro, personal and social perspectives.

3.5.1 Macro-Adaptive Approach for Adaptation of Knowledge Goals

The macro-adaptive approach defines general guidelines for adaptive teaching, and a curriculum based on content and knowledge type. This approach is based on an initial stage with a priori and a posteriori analysis of static data and explicit knowledge by teachers with experience working with knowledge domain experts and system engineers to design adaptive instruction, tutoring, feedback, and assessment systems based on pre-set dynamic learning pathways. Deepening the innovation of macro-adapted approaches requires the construction of adaptive knowledge representation methods in conjunction with cognitive semiotics, information processing theory, and cognitive load theory, corresponding to different phases of the learning task (Brandt, 2020). Different theoretical bases of knowledge, such as factual, procedural, and metacognitive, include knowledge, cognitive, and automatic schemas. Learners train their working memory through continuous editing of cognitive rules to enhance their long-term memory storage. Teaching and curriculum design experts combine theoretical and empirical evidence to identify effective methods of knowledge mastery and transformation. Learning systems, such as adaptive instruction, (intelligent) tutoring, adaptive educational hypermedia and recommendation systems, adopt macro-level approaches being developed with more advanced capabilities for learners (Sakkinah et al., 2022; Lamya et al., 2022).

3.5.2 Micro-Adaptive Approaches for Adaptation Assessments

The micro-adaptive approach involves on-task measurement with criteria and indicators that position teachers to assess how they track learners' behavior by providing scaffolding, including automatic prompts, corrections, and feedback. The behaviorist and zone of proximal development theories provide a basis for the micro-adaptive approach. The principle of instructional design is that learning in small steps based on the proximal development zone, combined with the stimulate response theory, reinforces learning through a process of trial and error. With this micro-adaptive approach, underpinned by practical work, learners engage in a gamified and immersive virtual laboratory to reinforce the learning experience. The modality for learning could be procedural learning with detailed units and knowledge points, combined with a personalized interactive scaffolding, adaptive heuristic scaffolds and emotional assistants (Lim et al., 2023).

Teaching and learning are delivered by teachers, pedagogy innovation researchers, system designers, cognitive psychologists, and data scientists who design pedagogical agents, develop analytic parameters, and capture a range of behavioral data generated by the learner's interaction with the system. Clustering these datasets to identify distinct learners' profiles has the potential to provide the evidence needed by the intelligent tutoring system or human teacher for redesigning adaptive scaffolding; and for adjusting the instructional styles and learning content based on difficulty levels and learning assessments. This type of adaptation strategy, with the implicit knowledge based on real-time tracking, combines learning analytics and data mining techniques to provide semi-automatic and intelligent automatic learning recommendations and feedback.

3.5.3 Personal-Trait Adaptive Approaches for Individual Development

Macro and micro-adaptive approaches may focus on the effectiveness of adaptive instruction and learning, whereas the learning experience should be enhanced through personalization and meaningful learning. Designing adaptive approaches based on personal traits requires extensive datasets, adaptive learning analytics, intelligent adaptation, and metacognitive navigation techniques. The sequence of individualized or customized learning activities is adapted to the learner through continuous differentiated analysis, formative assessment and summative assessment in real time. Indicators of adaptation include individual learners' knowledge goals, cognitive state, affective needs, learning preferences, etc., (Raj & Renumol, 2022). The theoretical underpinnings of the approaches are the Gestalt psychology of insightful learning, learning transfer, productive thinking, cognitive-psychological developmental theory of multiple intelligences, social comparison theory, (cultural-historical) constructivism, connectionism and connectivism (Siemens, 2017; Corbett & Spinello, 2020). The pedagogical principles are based on Maslow's hierarchy of needs, and motivation theory. Learners may develop professional knowledge, soft skills and adaptive capabilities through formal and informal learning, training and workshops. Adaptive learning continuously adapts and optimizes learning resources, scenarios, and intelligent textbooks, content, and pathways to suit different learning preferences. Learning preferences may be determined in the initial stages by tests or questionnaires filled out by learners when logging into the system, or it could be dynamically updated through continuous data analytics.

Adaptive metacognitive assistance, cognitive maps and intervention models such as adaptive navigators, mind mapping, and personalized learning analytics dashboards are provided to allow self-regulated learning (Carlon & Cross, 2022; Lim et al., 2023). The validation, development and innovation of adaptive learning with personal traits requires theoretical and empirical assessments based on the evidence and recordings of an individual lifelong learning cycle. Universities and educational institutions that only conduct short-term training might have difficulty accepting the feasibility of this approach.

3.5.4 Reflecting the Adaptive Approaches from A Social Perspective

The design of adaptive approaches in the context of constructing learning environments for the integration of professional expertise requires deeper investigation of learners' aptitudes and teaching needs. The availability of Massive Open Online Classes and sources (MOOCs) and Small Private Online Classes and sources (SPOCs) allows the possibility of flipped classrooms, ubiquitous learning resources, knowledge dissemination, and maker-space, and allows the learning modalities of learners acquiring 21st century skills to become asynchronous and flexible (Corbett & Spinello, 2020). The initial and continuous re-skilling and up-skilling programs are created with hybrid flexible measures to train learners to be more competitive and enable them to adapt in a professional work environment. The differences in learners' skill levels may be vast in a blended class, and the reflection of the construction and impacts of adaptive learning ecosystem is critical. Adaptive learning activities and simulation models should be built to allow competency-based, problem-based, project-based, and innovation-based learning in an open, intelligent and adaptive learning community. It is also an important step in fostering human intelligence-driven digital learning transformation. Cultivating interwoven intelligence is crucial in contemporary STEAM education. Hard and soft skills, and especially meta-thinking and meta-emotional intelligence, are gaining the attention of learners who might be involved in social innovation projects in the real world. Higher education institutions are expected to construct adaptive learning for personal and social needs. Learning log data are replicated not only to adapt to the individual but also the socio-economic outlook.

3.6 Implementation of an Adaptive Learning Ecosystem

The principal models of the adaptive learning system are: the learner model, the domain knowledge model, the instructional model, and the adaptive engine. This study focuses on the improvement, mainly through integration of adaptive learning analytics and assessment models, of the metacognitive auxiliary models and the feedback mechanisms to enhance both personalization and adaptivity. All of this is done through the development of each model in the adaptive learning ecosystem. Model analysis is done by studying: 1. adaptation indicators and criteria; 2. modelling methods and techniques; 3. challenges and opportunities for modelling.

3.6.1 Domain Knowledge Model

Domain knowledge is a knowledge engineering concept and can be defined in different ways based on the learning situation and modelling requirements. Domain experts may design concept maps, knowledge trees and skill hierarchies with different dimensions, difficulty levels and knowledge association points, possibly combined with adaptive testing and learning models, to create adaptive learning paths that meet the needs of heterogeneous groups of learners. The advances in modelling assisting and generation tools, including domain model acquisition tools, do not ensure perfect models, given that the creation and maintenance of domain models is a well-recognized bottleneck and remains a challenge in the use of automated planning. To innovate in the area of knowledge engineering systems, it is essential to develop the knowledge engineering planning model as an iterative process in the generation of effective plans, fed with an accurate model of an application in the planning engine (Lindsay & Petrick., 2022).

3.6.2 Learner Model

Learner modelling involves data elicitation, model representation, and maintenance, and it allows the system to provide the adaptation using the learning variables stored in the model. These variables can be classified into: conative, cognitive, metacognitive and affective categories. Well-defined and accurate adaptive criteria are critical for determining the effectiveness and sustainability of a learner model. Modelling approaches such as overlay, stereotype, Bayesian network, etc., employed algorithms and intelligent techniques, all mainly focused on the instructional contexts. The Open Learner Model (OLM) encourages learners to actively participate in thinking about and crafting their learning. It was designed as a suitable interface model which allows the visualization and transparency of knowledge and progress for the users including learners, peers, teachers, administrators, etc., (Brusilovsky et al., 2022b). It provides methods, techniques, and tools for promoting planning, navigation and other metacognitive activities that are important in the development of personalized adaptive mechanisms and for favoring deep learning (Hooshyar et al., 2020; Bull, 2020; Guerra Hollstein, 2018). Meanwhile the Open Social Learner Model (OSLM) integrates social comparison features that might improve learning motivation, achievement, and monitoring abilities, including self-reflection and self-assessment (Somyürek et al., 2020). OSLMs that use gamification and embodied cognition may be emerging as a research direction in the improvement of the adaptive learning experience.

3.6.3 Instructional Model

Adaptive Educational Systems (AES) include Adaptive Instructional Systems (AIS), Intelligent Tutoring Systems (ITS), and Adaptive Hypermedia Systems (AHS). Although several studies reveal that they are focused on the strategies of teaching, tutoring, learning adaptation and recommendation, they do not necessarily lead to better personalized adaptive learning. This is due to the accent being put on technological tools to the detriment of the pedagogical aspect (Apoki et al., 2022). The components in this model were found to have diverse functions, defining the rules to access the domain knowledge model in relation to learner models, and updating the learning design, methods, and activities based on the indicators and criteria. Challenging issues, at present, still include the handling of partnership among interdisciplinary teams. In the pedagogy innovation management model, it is important to redefine and reflect on the roles and impacts of pedagogues. What innovative didactic strategies, teaching competency, learning methods, techniques, and tools can suit the construction of personalized learning systems (Brühwiler & Vogt, 2020). Which logical feasibility, viability, and sustainability issues should be taken into account for reflection on learning impacts? How could adaptive deep learning activities be designed to prompt self-regulated, co-regulated learning and self-directed learning to allow the learners to cultivate the interwoven intelligence needed to become a domain expert. Is it feasible to integrate the competency or intelligence-based learning module into the instructional model for the training of vocational professionals and social career innovators?

3.6.4 Adaptive (Learning Recommendation) Engine

This adaptive engine is supported by machine learning algorithms. It allows the automatic generation of a presentation model and plays a fundamental role in implementing intelligent and adaptive approaches, techniques, or recommendation rules. The adaptive engine uses multiple criteria to make its recommendations, including adaptive sources based on learner models, adaptive targets, and elements based on content or instructional models. Then it adapts the content, assessment, and sequences for the learner (Shawky & Badai, 2018; El Guabassi et al., 2018; Mayrhuber & Krauss, 2022). The adaptive engine faces two main challenges: designing and implementing effective techniques; and using adaptive learning for a broader spectrum of combined disciplines. Future research directions for adaptive engines will require more competencies and transdisciplinary adaptive learning, involving the integration of multidisciplinary resources and interdisciplinary systems (Clemente et al., 2022).

3.6.5 Adaptive Learning Analytics and Assessment Models

Learning analytics play an important role in a wide range of actions. Firstly, they help with both describing learning performance and diagnosing knowledge mastery and cognitive abilities. Particularly important in predicting potential risks and prescribing both instructional decisions and recommendation resources, they ultimately help when trying to infer learning solutions. Adaptive learning analytics, as a subset of learning analytics, can analyze the above-mentioned variables about learning in addition to improving the overall implementation of personalized and adaptive learning (Sarıyalçınkaya et al., 2021b). In parallel, it attempts to incorporate personal cognitive and sentiment analytics into the multidimensional metrics of learning analytics. All this is in order to create a more accurate support for adaptive learning at an individual level. Personalized adaptive learning analytics dashboards are often used as a feedback tool to support the reflective phase of self-directed learning. Due to the lack of evidence to support the measurement of learners' metacognitive processes in open learning tasks, previous efforts on adaptive learning analytics for metacognitive enhancement appear insufficient. Nevertheless, strengthening the communication of technical and theoretical foundations among domain experts is a key action for addressing the main challenges.

3.6.6 Intervention Models: Metacognitive Auxiliary Models and Feedback Mechanisms

Adaptive learning analytics develop the basis for the implementation of different types of interactive intervention models. Self-regulated learning activities include metacognitive strategies such as planning, self-monitoring, self-reflection, self-adjustment, self-assessment, and self-efficacy (Kabir et al., 2022). An adaptive intervention engine promotes co-regulation by facilitating learning-based accompaniment, which favors deep learning by providing metacognitive auxiliary and feedback. The development of adaptive support methods is more conducive to improving learners' meta-intelligence and reflective ability. Moreover, meta-intelligence, including meta-consciousness and meta-emotional intelligence, is a key skill for cultivating learners' effective self-regulation and co-regulation learning, so that they can adapt to the knowledge innovation society. Due to the heterogeneity of learners, the feedback mechanism and its types may be based on individual needs for self-discipline, learning task orientation, or process orientation to generate the recommendations. Adaptive metacognitive scaffolding is based on knowledge development goals as well as the learners' cognitive and affective needs. Self-directed learners may benefit from different types of feedback, and adaptive learning systems should have the ability to automatically provide effective feedback. Meanwhile, the construction of metacognitive support and feedback adaptation combined with psychometrics and neuroscience might be attractive and effective in the development of future and modern learning techniques (Carlon & Cross, 2022; Ramírez-Mera & Tur, 2023).

3.7 CONCLUSION

The common reference focuses primarily on illustrating a dynamic framework that combines extraordinary measures and assessment guidelines for the development of adaptive learning. It was created through the synthesis of theoretical models, design approaches and implementation conditions, the reflections of relevant indicators, and criteria for the construction of a logical, feasible and sustainable adaptive learning ecosystem. It is oriented toward the perspective of symbiotic education, fusing the bodies of knowledge, ontology, epistemology, experience, and cognition (Kinsner, 2021; Nguyen et al., 2022).

In this synthesis, we began by interpreting the logical approach of learning theories to guide educators in designing adaptive learning activities to meet the needs of a heterogeneous group of learners. In parallel, adaptive learning and its analytic ecosystem are assessed by impact criteria such as compatibility, flexibility, etc. We conclude that effective adaptive learning systems need to have a broad range of learner evaluation methods, must obviously be feasible to implement, depending on the stakeholders' capabilities, and must be able to adapt to all the potential target learners. Given this, the ecosystem's performance is assessed through its capacity to adapt, mentor, recommend, and intervene. To improve its performance and quality, and to adapt to learners' needs, the constructed educational models will have to be transformed into adaptive learning models. Meanwhile, the main sustainability issue is the integration of technologies, which is nonetheless needed to ensure the reliability and variety of data analysis, as well as to enhance decision-making. This is especially true when adaptive learning development is affected by a great number of external variables.

CHAPTER 4. A MULTIMODAL LEARNING ANALYTICS FRAMEWORK

This chapter provides critical reviews on the definitions, objectives, methods of learning analytics and educational data mining. It aims to investigate insufficient interpretation of multimodal learning analytics and evaluation, for guiding significant adaptive learning construction. Qualitative thematic criteria are applied in selecting the studies, which identify multiple elements, machine and deep learning techniques in enhancing diagnose, prediction, prevention, recommendations and interventions. The indicators and variables involve in learning analytics and assessments including performance, (meta) cognitive (neuro) states, affection, motivation, (meta) knowledge or skills levels mastery; profiling learners' characteristics such as personal traits, individual needs, behaviors and learning outcomes; simulations of meta-physiological signals, bio and neuro feedbacks underpinned by biometrics; evaluation of technological adaptivity, learning adaptability, user satisfaction and learning risks etc., The goals are to leverage the effects of mechanisms on the design of precision learning and quality education, and to rethink how the results of multi-modal learning analytics affect the advancement of adaptive deep learning sciences. The values of research conducted include the improvement of design for a sustainable ecosystem, that is based on precision learning analytics and quality evaluation of dedicated individuals, organizations, communities, and relevant key indicators, interesting factors, potential variables of performance and quality. The objective of Education 5.0 is to create a human-centric, personalized, adaptive, inclusive and sustainable ecosystem that involves evaluating the impacts of reliable artificial and human intelligence towards improving the accuracy of measurements and evaluation. Adaptive learning research innovation communities are expected to integrate the approaches with an evaluation of variety, validity, veracity, volatility, variability, viability and value to increase the performance of interdisciplinary intelligent models, as well as trans-disciplinary frameworks.

4.1 INTRODUCTION

Learning analytics involves the assessment of the effects and impacts of didactics in which the educators give feedback to learners through measuring and deepening the learning process. The formative assessment as a diagnostic evaluation, which is used to timely monitor learners' progress and support adaptive learning to take corrective measures. It constitutes a variety of methods to describe mastery, learning needs, and academic progress and provide recommendation and intervention in order to realize an individual learning experience and success. Summative assessment verifies and certifies the effects of course content, impacts of learning activities, and the quality of teaching and learning based on the evaluation with predefined standards and benchmarks. It emphasizes the understanding of learning course difficulty and performance to develop the prescriptive, preventive and interventional measures. Learning Analytics (LA) is an emerging assessment technology, which selects important parameters and intelligent tools to profile learners' differences, predict learning performance, and factors that affect learning achievements. LA collects and describes the learning progress and results in detail through analysis based on hypotheses and evidence, it also supports dynamic monitoring and decision-making in the evaluation process. Although research on adaptive learning environments has increased, this field lacks a critical analysis of crucial factors in the reviews, that are deserved to be investigated significantly for constructing effective learning. Learning analytics lacks enough evidence to favor the effectiveness of strategic plans for precision education. In recent year, in the research communities of adaptive learning, there has been a clear progressive trend toward precision learning. The growing popularity of emerging AI, can be regarded as the feasible means to achieve the multi-modal precision and accuracy. This present investigation conducted a critical literature review to determine the most important goals and parameters in modeling and analysis, as well as the application and comparison of existing methods, tools and technologies. The purpose is to identify the definition, and application of LA and EDM and their interplays with learning sciences and quality of precision education. Indeed, the intersection of learning science and data analysis enables more sophisticated ways to support the construction of adaptive learning. As such, this chapter focuses on the review of the applications of LA and EDM techniques and methods in measuring performance including academic achievements, impacts of teaching and learning environments, prediction of risks, evaluation of systems' adaptivity as well as learners' adaptability based on adaptive learning sciences, for improving the users' learning experience, and enhancing the effects of education ecosystem. The literature review examines the current status of the application of Learning Analytics (LA) and Educational Data Mining (EDM), and their significance in the development of adaptive learning environments, because current research shows that there are needs of the advancement in this field. This review gives educators, including instructional system designers, pedagogical innovation experts, cognitive neuroscientists, teachers, and administrators, the perspectives in redefining the roles and regenerating their corresponding functionalities. It provides an updated picture of comprehensive learning analytics tasks, data mining application methods, techniques, tools analysis to construct an effective education ecosystem, which allows consideration of algorithms as the didactic tools in establishing more adaptive precision learning paths.

To provide insights into the advantages and values of learning analytics and educational data mining in the construction of an adaptive learning environment, a critical synthesis of review is conducted to reveal the status of current and ongoing status, emerging issues, and research directions of using precision adaptation in personalized and individual learning. The research questions in the following guide this critical synthesis:

• What are the primary research purposes of using the approaches based on learning analytics and educational data mining for precision adaptive learning? (e.g., the scope or level of profiling, diagnosis, prediction, prevention, recommendation, and intervention)?

• What are the analytics approaches and algorithms employed for resolving what types of (learning) problems?

• Are there significant relationships among these aforementioned categorical variables (data types)?

• What are the emerging trends of precision personalized adaptive learning?

4.2 METHODS

4.2.1 Literature Review

For this review, we selected peer-reviewed articles employing learning analytics and educational data mining techniques for the construction of adaptive learning, published in journals that are indexed in the Web of Science and Google Scholar databases. The highly cited articles are selected in terms of innovation and quality. Personalized learning and precision education gained popularity in the development of adaptive learning in the last decade, we set our research to articles published from 2016 to 2024. We further limited the document type to journal or early access articles written in English to ensure the consistent quality of selected studies. The keywords used for this search included "learning analytics", "educational data mining," "adaptive learning", "personalized learning" "individual learning", "precision learning", "machine learning", "deep learning", "learning performance", "learning style"," cognitive states", "knowledge level tracking", "emotional status", "learning behavior", "technology acceptance", "learning risks". Based on the above search parameters, a total of 142 articles were retrieved. Throughout the demonstration of the processes of selecting the eligible studies for this investigation. We then screened the articles by reading the titles and abstracts. Those studies that matched our inclusion criteria were retained. The inclusion criteria include: (1) review paper, empirical studies, (2) in a learning analytics setting, (3) using data mining techniques and machine learning algorithms, and (4) measuring variables such as performance, behavior, cognition, emotion, motivation and metacognition. The study begins by interpreting the definition of learning analytics and educational data mining, and the research focus is limited to English articles that contain critical analytics indicators, which are described in the above keywords. In the second stage, a total of 121 articles were eligible to be included in the evaluation for implementation of multi-modal learning analytics towards adaptive learning. A total of 18 articles were selected for the performance analytics and impact or influencing factors measurement. A total of 16 articles were selected for the analytics of cognitive states and knowledge level tracking. A total of 30 articles were selected for the analytics of learners' characteristics profiling, adaptive learning recommendation, and improving precision prediction. A total of 12 articles were chosen for analytics of behaviors. A total of 17 articles were selected for the analytics of sentiments and emotional states. A total of 8 articles were chosen for the learning environment experience analytics. A total of 10 articles were selected for the analytics of risks and prevention measures. After applying the selection criteria, the final dataset comprised 142 articles.

4.2.2 Coding Scheme

To analyze the current status and future trends of machine-learning-based adaptive learning, all studies were qualitatively coded. The coding scheme consists of categories such as learning analytics and data mining purposes, performance, individual differences, cognitive states, knowledge level, emotional status, user behaviors, technology adaptivity and acceptance, learning risks and major findings in learning adaptability.

As suggested by Yang et al., (2019), the coding for the research purpose includes diagnosis or profiling, prediction, treatment or intervention, prevention, and recommendations.

The coding for general information comprises publication year, analysis parameters, variables, objectives, and data source. The coding for the learning environment is mainly by online or blended learning.

The interdisciplinary domain has gained increasing prominence in the past decade.

The coding for a domain that is in the subject of STEAM. This field focuses on sequencing and targeting learning in terms of precision adaptation and recommendation, which places great emphasis on data-intensive digital technologies (Williamson, 2021).

In addition, the topics are often step-based, and well-defined problems, where, machine learning tools and techniques can be relatively easily employed (Humble & Mozelius, 2022). The coding for learners' educational level is diversified.

Finally, among the coding scheme, learning analytics parameters, machine learning algorithms, evaluation and validation of algorithms are coded with multiple responses as the review evaluates several indicators and relevant algorithms, evaluation tools, and validation approaches.

4.3 Learning Analytics (LA)

Current research presents the diversified definitions in LA and shows the confusion. Thus, it is particularly important to redefine and distinguish the differences and interplay between them to establish an extended architecture and framework for the implementation of adaptive learning plans. This paragraph describes the definition of LA in different contexts including the disciplines, functions, requirements and horizons of stakeholders. LA is an emerging field in which sophisticated analytic tools are used to find the solutions in implementing effective learning strategies and to improve performance. It is the subject of collecting, measuring, analyzing, evaluating and reporting data through various traditional and advanced methods, techniques and tools. It allows users to discover valuable feedback about instructions and learning needs, it should optimize user experience, improve the learning process as well as the environment in which it occurs, through the acquisition, interpretation, and contextualization of the data in educational resource libraries such as the Learning Management System (LMS). Learning analytics is a multidisciplinary field which involves different subjects including statistics, psychology, learning science, social science, brain and computer science. When it is defined from certain domains, included the application of artificial intelligence, machine learning, EDM, recommendation systems, and personalized autonomy to adapt the learning process and advance the science to enhance the quality of precision education. When LA is defined from the perspective of data analytics, it is about hypothesizing, predicting, discovering, enhancing and optimizing adaptive learning and its environments through data mining, information retrieval and visualization. It solves educational challenges by integrating technology, academic and social factors and focuses on adaptive assessment and evaluation to provide crucial feedback and promote decision-making by involved stakeholders including educators, students, curriculum developers, researchers, educational institutions. LA is an important field of technology enhanced learning (TEL), which facilitates both the innovation and maturing of learning technologies, which in turn promotes the development of analysis in the learning environment and improvs learning through the analysis and display of user data. The latter is rooted in the continuous increase in the amount of user data and is associated with management methods that focus on quantitative indicators. LA concentrates on the overall system which supports human intervention, it aims to provide the reports that can use human-centric intelligent judgment and explores solutions among interactions to bring the benefits for educational and learning stakeholders. Furthermore, it strengthens the construction of a management system through the integration of the hypotheses, methods and techniques for acquisition of information and knowledge discovery to assess how the learning system works from different scenarios and how the process of learning can be improved and further developed based on both evidence and science.

Adaptive Learning Analytics (ALA) can be defined as a subset of LA, which provides solutions and possibilities for the more customized and individual learning paths. ALA plays an important role in adaptive learning system models as it supports precision learning and intervention models to improve learner performance through provide more individual learning path and feedback. Thus, ALA is usually defined in terms of personalized adaptive learning methods and models. It is significant to optimize the precision learning environment in which learning takes place through individual adaptive approaches.

4.3.1 The Objectives of Learning Analytics (LA) and Its Adaptation

The adaptive learning environments based on LA include macro and micro adaptive methods, adaptive processing methods, constructivist and collaborative methods and so forth. Adaptive Learning Analytics (ALA) use data and methods to analyze the engagement, performance and learning strategies. LA provides the evidence in evaluating and modifying the course teaching, creating the adaptive learning sequences, and revealing the feasibility and logic based on impact measurement of the learning process and reflecting the most important variables in the Adaptive Analytics System (AAS) models. It involves learning, monitoring, modeling, analyzing, adjusting the learning field of interest, course analysis, personalization and adaptability (Mah et al., 2019). ALA focus on the investigation of human-centric solutions based on data mining and analytics for different types of adaptation, including adaptive content, adaptive assessment, adaptive sequence and adaptive experience. Adaptive content is about how to design and present knowledge content to meet the individual or group needs and learning objectives; adaptive assessment evaluates learners' knowledge mastery and learning effects based on practices and benchmarks tests; and adaptive sequence involves the use of advanced technologies include machine learning techniques to enhance teaching and learning processes and create the optimized adaptive learning paths; adaptive experience involves the analysis of how learning needs, teaching and learning behaviors, strategies, cognitive ability, emotional states, scenarios and circumstances affect the adaptive learning and user experience.

ALA and an innovative teaching environment promote the transformation of learning activities into learning experiences. The construction of the teaching environment based on multi-dimensional ALA and the design of the ALS with humanized experience act as the core for the users' experience, interactivity, learner's learning paths, cognitive ability, learning habits, emotional responses, human-computer collaboration. LA adopt different principles to interpret data at different levels for different audience groups. It serves learning, insights and development through the macro, meso, and micro levels from organizations to institutions and individuals providing stakeholders with a view of teaching and learning in a specific environment, enabling them to become the collaborators. From a learner's perspective, the objectives of LA are to predict and improve performance based on individual profiles' modeling, which allows them to check their profiles, to complete learning path planning and selection. To improve their understandings of courses contents, providing personalized real-time counseling, customized learning resources that suits the needs of those in learning difficulties become necessary.

Throughout the detection of improper learning strategies or behaviors, the discovery of their cognitive processes, emotional status, thereby, the provisions of effective scaffolding and adaptive feedbacks are influential in enhancing their self-reflection and self-awareness. LA provides education sector with new visions to understand students, thereby using limited resources effectively. It can also improve learning practices by changing the way it supports the learning processes. The objectives of LA from the perspective of educators are to help them improve teaching guidance, materials, supplementary activities and grading accuracy through continuous modeling including teaching modeling and knowledge domain modeling etc. LA allows the practitioners and system to collect the information about when they provide the interventions and the relevant learning resources for the students who encounter difficulties. The possibilities include prediction, modeling of learners' files, coaching needs, learners' performance, improvement of the accuracy of grading and evaluation, learning theoretical support, retention and stimulation of the learners' interest and motivation level, thereby affecting retention rates. The objectives of LA from the perspective of administrators are to improve the accuracy, practicality, and applicability of academic decisions, the completion success rate and assessments of performance and quality. Further objectives are to determine useful frameworks of adaptive learning, and to integrate the methods and technologies of learning components including objectives, content, strategies, evaluation, digital learning resources and tools for improving the effectiveness of adaptive processes and learning outcomes (Surahman et al., 2019), enabling educational and learning practitioners to carry out learning activities in the optimal way. Eventually, integration of educational resources from institutional-level resources to test the relevant hypotheses of the adaptive learning process and teaching efficiency.

4.3.2 Educational Data Mining (EDM)

EDM is an interdisciplinary field that combines the themes including computer science, statistics, and education etc., it is deeply influenced by the machine learning and predictive training method. It is about the automated paradigm of data analysis, focusing on the development, research and application of computerized methods to detect patterns in a large amount of educational data (Romero & Ventura, 2019; Papadogiannis et al., 2024). The research of EDM technology focuses on the description and comparison of computational techniques commonly used for the analysis of unsupervised and supervised learning algorithms. It aims to provide automatic discovery of learner models or prediction of learning outcomes. Data mining technologies find new patterns in data and develop new algorithms and or new models, while LA applies known predictive models in learning systems. To get the relevant results, it is important to understand the data and analyze the components and the appropriate precision algorithms. The process can be iterative when the results need to be improved and the questions were not answered, in which case it is necessary to modify the parameters, discover new patterns in data, modify corresponding algorithms and find new technical solutions.

Previous studies reviewed EDM as the techniques, which underpin learners profiling, modeling user behavior, performance, evaluation, learner support, feedback, knowledge tracking and teaching support (Pena-Ayala, 2013; Chango et al., 2022; Aulakh et al., 2023; Peña-Ayala, 2023). The applications of EDM including user modeling, which incorporates information (e.g., prior knowledge, cognitive levels, motivation, metacognition and attitudes), to predict future learning behavior; domain modeling characterized by the learning content and optimal instructional sequences and teaching support. It focused on measuring the impacts of different types of pedagogical support that can be provided by the computational system and finally advancing the scientific research of adaptive didactics through the building of knowledge about learning theories based on the models of learner, domain, and adaptive technologies (Backer & Yacef, 2009; Papadogiannis et al., 2024). Building the models based on the personal traits as different variables of students influences the learning and teaching process. For instance, discovering the learning sequence activities that are suitable and effective for learners, improving the learning progress through the observation of the features of learners' actions and behaviors, finding out the indicators or predictors which predict the course grades and success associated with emotional states, motivational factors, satisfaction, engagements etc. Finally, finding out and redesigning the learning system to be more adaptable and effective for learning and teaching. Bienkowski et al., (2012) divided the EDM into the five models: user knowledge modeling represents the process of accumulating users' data to improve the interactions between students and learning systems, which has been adopted to build adaptive hypermedia, intelligent tutoring systems, recommender systems and expert systems. The models collect the user's specific data such as knowledge and skills, the system adapts the required needs of students based on those conditions to provide the personalized learning paths. The method for tracking the knowledge is the Knowledge Tracking (KT) model which uses a Bayesian-network for predicting or estimating the probability that students master the knowledge. The machine learning approach incorporated models of guessing and slipped into predictions of future performance has been introduced and increased the accuracy of the predictions above 48% (Corbett & Anderson, 1994); User behavior modeling in education is about the collection of the data on engagement and learning behaviors of students in learning systems. For instance, the time spent and numbers of trials on the exercises, the times they tried to click to get the correct answers etc. These behaviors indicated the mastery of knowledge or skills of students and influenced their grades, the collected data provided the prerequisites for a more accurate estimation of students' performance and recommendations for the teachers to make educational interventions; user experience modeling is important to improve the efficiency and effectiveness in higher education institutions. The measures include the traditional analytics methods, the surveys, case studies such as periodic surveys of motivation and areas of interests. The objectives are to improve retention rate and foster academic success. Harnessing data-capture mechanisms from systems and communication tools enables the improvement of educational relevance throughout entire life cycle from progression containing grades, knowledge, skills, to graduation and employment; thus, user profiling is critical in describing the important characteristics of students based on demographic data such as background, preferences, interests, learning goals. The user model framework relies on interaction logs to collect the behaviors of students and the institutions use of profiling technologies based on this information and data to predict the learning styles. Classification and clustering are used to group students together into study groups or other joint learning activities; domain modelling investigates how learning is affected by differences and how a topic is divided into the concepts at a particular level of generalization, which has been adopted as the approach to better serve learning and instruction in the system. Learning curves can be used to drive changes in the user model for personalized learning environments.

EDM research aims to improve learning effects and experience through predicting the performance, providing feedback by testing educational theories and formulating new hypotheses. Perceiving, understanding models, analyzing, adjusting parameters and identifying the predictive behaviors that students may perform in specific situations allows teachers to mine the types of data needed to change the curriculum design at the cohort level or the evaluation format from classic statistical analysis of quantitative data sets to neural network experiments to achieve goals that will greatly help improve students' success and retention rate, and optimizing students' learning experience (Romero & Ventura, 2013; Olmos & Corrin, 2012; Romero & Ventura, 2020).

4.3.3 Learning Analytics (LA) and Educational Data Mining (EDM)

This paragraph summarizes the similarities and differences between LA and EDM in adaptive learning systems. EDM is a subset of the LA, in addition to computer science, statistics, psychology, and learning science, LA is also related to information and social sciences (Bienkowski et al, 2012; Baek & Doleck, 2023)**.** EDM performs exploration on differences, similarities and detections etc. While LA informs and authorizes teachers and learners. LA focuses on the process of influencing learning, while EDM focuses on discovering knowledge from all educational data sources generated by individuals and groups. It is supported by the institutional framework, using statistical data to help educators track the performance and difficulties of students and adjust the needs of learning activities, predicting the realization of the educational course goals, so that the design of the learning environment can adapt to the teaching process, resources and activities. Siemens & Baker, (2014); Baker & Inventado, (2014), summarized five key differences between EDM and LA, which emphasize the focal points on sentiment analysis, impact analysis, social network analysis, influence analysis, discourse analysis, and learner success prediction. Learning involves intelligent programs, perception prediction, conceptual analysis, meaning building model and system intervention. Educators and researchers use EDM for machine exploration, automatic adaptation and discovery for further analysis and judgement, while they use LA to achieve an innovative curriculum, teaching methods, performance prediction and impact analysis. These two research fields are complementary in terms of the learning process method. LA adopts the overall framework in the entire system and strives to fully understand and analyze its complexity and application. EDM simplifies the system and is more about the application of technology and methods, exploration of the components and their relationships. It analyzes and finds new patterns in data, and modifies corresponding algorithms. LA empowers students and teachers with EDM using classification, clustering, Bayesian modeling, relationship exploration, model discovery, visualization and other technical methods. The table below briefly described the differences of definition, characteristics, objectives, applications, methods and techniques and between learning analytics and educational data mining.

Table 1. The differences between learning analytics and data mining

	Learning Analytics	**Data Mining**
Definition	Human-centric judgement for collecting, measuring, analyzing, reporting, and evaluating educational data but also processes and	Automated paradigm of data analysis to detect patterns, which combines the themes of statistics, machine learning,

	impacts, which involve data mining, statistical techniques, modeling analysis, hypothetical decision support, psychology, learning theory science and social science.	predictive training methods, education by analyzing components, finding new patterns, modifying corresponding algorithms.
Characteristics	Influencing learning processes, descriptive, predictive, prescriptive or preventative, and explanatory.	Machine exploration and discovery of the knowledge about differences, similarities and relationships, detections, parameter estimation, automatic adaptation.
Objectives	Measuring the impacts of pedagogical support, adjusting in teaching guidance and improving learning environments by planning, scheduling, personalization and adaptation. Advancing the scientific research by verifying learning theories in authentic environments.	Monitoring, prediction, modules modeling, and adaptive sequence activities through discovery of patterns/styles. Optimizing learning, recommendation systems based on algorithms, determination of accuracy including comparison with a reference to check the quality of predictions.
Applications	Development, adjustment of models, determination of framework, perception prediction, conceptual analysis, system intervention.	User profiling, cognitive states and knowledge modeling, behavior modeling, user experience, domain model.
Methods & Techniques	Social network analysis, process-oriented analysis, content analysis, sentiment analysis, visual learning analysis, multimodal learning analysis, event sequence analysis, time series, attributes treatment, dashboard and discourse.	Machine learning algorithms, anomaly detection, process mining, text mining, visualization, Bayesian knowledge tracing, correlation mining, sequential pattern mining and distillation of data for human judgements.

4.3.4 The Values of Learning Analytics and Educational Data Mining

LA and EDM identify the factors as predictive indicators of performance and explore their predictive value and capabilities by tracking changes in actual behavioral data. EDM and LA tools are used to evaluate learning processes, performance, create adaptive and collaborative learning, as well as to develop powerful and accurate learning services for adaptive learning designers and practitioners. Romero & Ventura, (2020) pointed out that these two data-centric research fields are usually interchangeable. Both EDM and LA have similar goals in focusing on the intersection of learning science and data-driven analysis and the extraction of information from educational data that supports the adaptation and customization of learning paths for learners and assists the educational decision-making for stakeholders in improving performance and achieving better quality in education based on evidence and experience.

The table below summarizes the main advantages and values in applying the learning analytics and educational data mining which generated ideas in implementing data analytics and evaluating the impacts in the educational ecosystem.

Table 2. The key advantages and values in applying LA and EDM

Advantages	Values
Creating the alerts for stakeholders, users modeling, development, adjustment of models, domain modeling, learners analysis, courseware construction, planning and scheduling, allocation of resources and parameter estimation	Determining the indicators of performance, exploring their predictive value and capabilities by tracking changes in actual behavioral data and developing a more adaptive system to monitor the progress, evaluate and adjust strategies to improve performance.
Allowing the analysis and evaluation of performance, dropout or retention, design of self-study, interaction with collaborative learning, simulations, visual analysis, feedback, recommendations (Aldowah et al., 2019); improving the accuracy of profiles, and adaptability and personalization of subsequent content. Supporting multimodality and mobility to form a picture of what, why, how, when and where (Romero & Ventura, 2013; Grivokostopoulou et al., 2014; Romero & Ventura, 2020).	Customizing the learning process by modeling adaptive mechanisms for addressing the needs of users; modeling the psychometric framework; ensuring pedagogic support and scientific research that can be measured and improved by educational science theories, and hypotheses that can be formulated and tested (Baker & Yacef, 2014).

4.4 The Common Reference Framework of Multimodal Learning Analytics

Learning analytics facilitates and improves the construction of adaptive learning environment. While it may have precision issues of implementation in achieving adaptive learning. This is mainly due to the heterogeneous characteristics of learners. An intelligent adaptive learning system or tool may be flexible and versatile. It is capable of accommodating a wide range of short-term goals. Correspondingly, it needs to be orientated to small-scale or a combination of both adaptation to the short- and long-term goals of the learner. Precision learning encourages the construction of individual adaptive learning paths to optimize the deep learning experience.

Learning gains, learning outcomes, and academic achievement are often used to measure learner performance. Learning performance analysis focuses on measuring the overall and individual performance of learners and the factors that influence learning. Behavior, engagement and interaction among participants may influence learning performance from different degrees. Behavioral measurements are usually involved in recording logins, number of exercises, learning and interacting time. Furthermore, intelligent companion, chatbots allow educational practitioners to leverage emerging devices, natural language processing to recognize facial expressions, identify gestures, and detect individual and overall emotional elements and states.

Learning experiences environment is primarily constructed and updated based on learners' needs, including technology acceptance, ergonomic adaptability, the adaptation in learning content, learning activities, and knowledge level. Although, satisfaction investigation questionnaires are often used as a metric to evaluate user experience. The advanced intelligent virtual learning tools are developed to track learners' embodied emotional states and improve the learning experience. Eventually, the main criterion for learning risk analytics is to detect extreme values and provide appropriate prevention, intervention and viable management measures. These extreme values may reveal inappropriate behaviors, unlogic learning strategies. Learning risk analytics focuses on describe users'engagement, cognitive processes, learning performance, predict proficiency, mastery, risks, and diagnose learning difficulties etc., optimize learning path and prescript standards of learning.

4.4.1 Learning Performance

LA analyses learning processes, which can improve individual and collective performance, assisting institutions in formulating a framework for adaptive learning support, facilitating a decision-making procedure geared towards sustainable education (Wu & Lai, 2019 ; C. C. Y. Yang et al., 2024). LA is expected to enhance educational quality by identifying more factors that can influence levels of performance. It aims to solve common objectives and challenges surrounding motivation, diverse learners' backgrounds, positions, and resource constraints etc., Performance analytics dedicates in the evaluation of precision learning impacts considering quality education with well-designed pedagogical contents, technological impacts and learning adaptability. It then provides insights beneficial for decisions-making and actions-taking of multi-disciplinary actors in improving adaptive learning systems, models and intervention mechanisms.

The evaluation of performance could be complex when it is considered from multi-perspectives across micro-level, meso-level and macro-level of adaptation. For instance, when the factors or variables are measured for adapting to individuals'needs, they can be concerned with improving self-regulated-learning (SRL) experience to enhance practices and feedback loops underpinned by cognitive psychological construction (C. C. Y. Yang et al., 2024). LA aims to measure the personal traits, attributes, cognitive, affective, motivational and metacognitive factors and so forth. When the criteria and models are developed to adapt in pedagogy innovation, they are related in improving knowledge circulation, collective learning performance including learning outcomes, academic achievements, interdisciplinary intelligence, and abilities to apply transdisciplinary approach to specific real-life projects. When the adaptive indicators are designed to flourish human well-being system considering social-cultural adaptive elements, knowledge sharing and meta context transformation through opening adaptive socially sharing innovative activities to achieve efficacy learning stakeholders' co-creative value by muti-channels communication and muti-models interaction and so forth to address urgency lifelong challenges and environmental issues. Thus, the performance could be measured based on all of these factors and levels by adaptive learning technologies to reveal relevant goals, factors, variables, subtle hidden patterns. However, the interpretation is being more beneficial from investigations of multidisciplinary knowledge, interdisciplinary intelligence and transdisciplinary approaches. Advanced studies and investigations reveal that learners' performance in academic knowledge and meta levels of knowledge, interwoven intelligence development could be influenced by social, environmental, organizational, individual psychological and cognitive neuro factors. The results of effects and added values can be different due to factors such as backgrounds, goals, working positions, social engagements and motivational beliefs such as intrinsic and extrinsic goals-orientation. These elements influence actors' participation, success and satisfaction in hybrid flexible adaptive learning environments.

Adaptive LA communities and stakeholders often employ different techniques for exploring viable, efficacy system impacts, optimizing learning performance by modelling users' profiles or learning modules, recommending personalized adaptive learning support, discovering adaptive elements, optimal settings and paths to underpin individual and collective performance by intelligent adaptive methods.

Adaptive LA technologies aim to accelerate educational, pedagogy, instruction, teaching and learning performance and quality from different dimensions and levels. It can dynamically adjust learning strategies, contents, sequences and evaluation by intelligent personalized adaptation or pre-set standards for formative and summative assessments to accommodate individual's needs and knowledge assimilation. It employs appropriate descriptive, predictive, diagnostic, prescriptive analytics and assessments of learning stakeholders' explicit and implicit variables such as cognition, emotion, interests, strategies, achievements, knowledge, and competences. These measurements and feedbacks generated can therefore contribute to the optimization of external subjective learning activities as well as improvement of internal objective (meta) cognitive mechanisms construction. These various adaptable and personalized interventions mechanisms include learning abilities and deep learning strategies, generated from execution functions, (meta) cognitive (behavior) monitoring and meta-control, bio and neuro adaptive feedbacks, metacognitive knowledge (e.g., higher-order thinking and cognitive functions), offline metacognitive knowledge (e.g., judgements, reflections, resilience, self-efficacy), as well as, adaptive collaboration, socially-shared learning activities as diverse predictors.

A series of experiments suggested that demographic profiles, personal traits and learning performance features are among critical indicators when predicting (academic) outcomes and successes. The key performance and quality analytics for adaptive goals are to increase prediction accuracy, automatic grading, learning precision and effects. For instance, minimizing errors in predicting test results; measuring similarities between learners' abilities and interests, dividing them into distinct groups, discovering optimal learning peers or patterns; grouping or profiling, characterizing learners for models modelling, mechanisms' construction; improving effects of recommendation. A wide range of studies indicated that mixed effect models with multiple machine learning techniques, natural language, brain-image processing and neurocomputing for well-being learning showed improved performance but also unverified effects respectively compared with traditional methods.

The table below is a summary of the objectives of learning analytics with corresponding tools and data mining techniques for predicting and evaluating performance, particularly in educational achievement, and the variables and factors which influence the performance according to the reviews.

Table 3. Performance analytics and evaluation

Category	Objectives	References	Tools, Techniques
Performance analytics & Achievement evaluation	Estimate the learning model and or (hybrid) prediction of academic performance.	S. J. H. Yang et al., (2018); Albalooshi et. al., (2019); Al-Tameemi et al., (2024).	Multiple Linear Regression (MLR), principal component analysis (PCA); Single Linear Regression and MLR; Feedforward Dense Network (FDN), Random Forest (RF), and Decision Tree (DT).
	Evaluation or (early)prediction of student performance and grade.	Bharara et al., (2018); S. Hussain et Khan, (2023); Burman et Som, (2019); Dias et al., (2020); Lincke et al., (2019); Alnasyan et al., (2024);	K-means clustering; Decision Tree (DT), Artificial Neural Network (ANN), Support Vector Machine (SVM); ANN, DT, Naïve Bayes; GA based DT; SVM; RNN; CNNs, DNNS, and LSTMs; Multinomial Logistic Regression, Decision Trees,

		Tiukhova et al., (2024).	Random Forest, K-Nearest Neighbors, Naïve Bayes, and Support Vector Machine.
	Model evaluation included the accuracy metrics and performance measures.	Mubarak et al., (2021); El Aouifi et al., (2021).	Linear Regression, Logistic Regression, Gradient Boosted Tree, XG Boost, DNN, Bayesian Neural Network, Rich Context model (RCM).
	Behavior analysis and prediction of the effects on performance.	Neha et al., (2021).	DNN(LSTM)K-NN, Multilayer Perceptron (MLP). DNN.
	Identification of predictive variables, analyze and evaluation the nonlinear interaction between cognitive and psychological aspects affecting students' academic performance.	Altabrawee et al., (2019).	ANN, NB, LR, DT.
	Identify the factors, variables and forecast their relationships against performance. Prediction of engagement, assess the effects on performance.	M. Hussain et al., (2018); Stan et al., (2022).25/11/2024 21:23:00	DT, JRIP, J48, GBT, CART, NBC.

4.4.2 Cognitive States and Knowledge Level Tracking

The evaluation of cognitive performance should offer adaptive learning stakeholders the evidence, feedback, as well as, insights, to interpret the changing nature of learning phenomena and the variability of adaptive elements. Predictive, intelligent, adaptive, and generative technologies might be employed within the context to improve adaptive content structures and adjust sequences, or strategies to meet learning needs. These benefit designers, engineers, or practitioners in constructing feasibly personalized interventions, learning optimization, and (meta) cognitive auxiliaries. It, in turn, facilitates learners' cognitive processes, improving cognitive functions, and higher-order skill' development.

The key aim for adapting cognitive processes is to increase self-regulated learners' success rate in acquiring adaptive knowledge, meta-cognitive control, as well as self-efficacy skills. Adaptive learning technologies, such as deep learning analytics, could assist in enhancing the validity and viability. For instance, (deep) knowledge tracking and cognitive processes monitoring, which can dynamically model learner' profiles, levels of mastery, and adaptive cognitive patterns by analyzing their interactions and assessing factors (e.g., (meta) cognitive strategies, operational functions) that influence knowledge components acquisition especially for higher-order skills proficiencies.

Nevertheless, there remains a wide range of literature that reveals the limitation of traditional knowledge-tracking techniques, which often neglect human' hidden cognitive patterns, development of cognitive psychology, efficacy law, and change of behaviors. Therefore, adaptive learning practitioners are encouraged to combine optimized deep learning solutions and technologies with more appropriate and accurate theoretical models, to further promote the progression of knowledge, and enhance the interpretability of meaningful cognitive neuro-adaptive mechanisms construction. The investigations on artificial intelligence's (AI) comparability with human intelligence, play pivotal roles in providing theoretical accounts of modeling methods for consciousnesses, knowledge, and capacity building. It helps explainable AI systems infer humans' beliefs and needs in AI's operations and provide human-centered explanations to enhance the construction of mutually responsive, adaptive mechanisms for generating interwoven intelligence.

The optimization of modeling approaches for domain knowledge, individual-specific knowledge types, and cognitive variable analysis models benefits from advancements and innovations in various adaptive theories and technologies. The criteria for these analysis and evaluation tasks may be constructed based on factors (e.g., knowledge goals, prior experience, cognitive states, behaviors), that significantly facilitate adaptive learning construction. In addition to traditional techniques, emerging approaches of knowledge tracking, knowledge construction, knowledge space and progressive theories (Sun et al., 2024). For instance, multiple knowledge concepts based on theories of cognition, metacognitive physiology, cognitive neuroscience, multidimensional item response theory (MIRT) (Zanellati et al., 2024), and innovative heterogeneous graph-based

Knowledge Tracing method with spatiotemporal evolution (TSKT) are gaining attention and popularity (H. Yang et al., 2024). These novel techniques are becoming prominent for tracking knowledge levels and cognitive states to address challenges and limitations in deep, complex learning processes and adaptive learning design.

Knowledge tracking and construction in spatiotemporal evolution, refers to the process by which cognitive training and problem-solving, which require continuous iterations of exercises and tasks, result in the construction of diverse knowledge graphs, conceptual associations, and skill development within hybrid models in heterogeneous learning environments. Knowledge space theory asserts that learning or exercising is not an isolated activity. Adaptive learning technologies may integrate theories of dual-channel information processing, cognitive load, zone of proximal development, metacognitive flexibility principles, for facilitating interpretable and sustainable methods in knowledge mastery or skills proficiency tracking, cognitive state assessments, and interventions. For instance, the proposed Progressive Knowledge Tracing (PKT), inspired by theories of constructivist and item response, which modeled cognitive processes into relatively independent but progressively linked-stages. It decomposed the learning process into three stages: conceptual mastery, problem-solving, and response behavior. Compared to existing methods, PKT incorporated interpretable parameters, grounded in meaningful educational theory, proved robust reasonable interpretability (Sun et al., 2024). Hidden Markov models, factor analysis models, and deep learning-based models, have been widely adopted in the modelling learners' models. The main representative is the Bayesian Knowledge Tracing (BKT) model, which uses the network to describe and model learner's knowledge status and mastery levels. It is derived by adding latent variables and posterior data through continuous decoding the relationships between learners and knowledge items. Bayesian neural network is deep learning model that combines the Bayesian method and the characteristics of neural networks to automatically extract features and perform complex pattern recognition. Deep learning tracking model, which integrates cognitive science and behavioral theory, and combines memory network, regression neural network, and Residual network for implementing deep modeling learning behavior (F. Ma et al., 2024). Learner's prior knowledge could be incorporated into the attention mechanism to capture the cognitive differences and evolution of cognition. A multi-layer context-aware deep knowledge tracking (MLC-DKT) model is introduced, which involves multi-layer context representation methods of knowledge concepts and exercises. Then, the calculation method of similarity effects between contextual information helped estimate the learner's knowledge status are developed. In a learning performance prediction module, the guessing and sliding factors in the cognitive diagnosis model, that were introduced to optimize the MLC-DKT model, which further improved the performance of the KT model and enabled the predictions more interpretable (S. Zhang et al., 2024). Moreover, the Hidden Markov Model (HMM) uses time series data to find learners' cognitive state transitions for designing LA dashboards, to help promote problem-based learning. The preliminary results showed that the model had high accuracy and was consistent with related theories, indicating that the model provided interpretable information.

Advanced computational models and brain-inspired intelligence provide stakeholders with the means for deeper and more precise learning using adaptive measurements and biometrics for exploring and building upon specific cognitive neural systems and brain and mind activities. These intelligent adaptive mechanisms may enhance the execution functions of certain higher-order cognitive operations, optimize (meta) cognitive processes ; Liu et al., 2022; Zhang et al., 2024). Multi-Voxel Pattern Analysis (MVPA) has enabled a novel and complementary approach to the study of the human mind, and in particular questions regarding information representation in the brain. Modeling cognitive states involves machine learning algorithms to classify categories of information represented in the brain during encoding and retrieval stages of memory processing.

The results and simulations showed that the proposed algorithm provided accurate and robust classification of cognitive processing based on the corresponding distribution of neural activity patterns in the brain (Zhang et al., 2024).

The table below describes the methods and objectives for predictive and normative analytics, adaptive and user-generative deep learning for learners' cognitive neuro status, knowledge components acquisition, changes as well as levels of cognitive abilities.

Table 4. Cognitive states and knowledge level tracking

Category	Objectives	References	Methods, Tools, Techniques
Cognitive states & Knowledge level tracking	Classify categories of information represented in the brain during memory processing, modeling of cognitive state.	Arroyo et al., (2014); Zhang et al., (2024).	Companions and progress report; Multi-Voxel Pattern Analysis (MVPA).
	Predict and assess of cognitive states, levels in the mastery of knowledge and skills.	Pelanek, (2017); Zanellati et al., (2024); H. Yang et al., (2024); Sun et al., (2024).	BKT; Logistics Regression; Multidimensional item response theory (MIRT); Knowledge Tracing with spatiotemporal evolution (TSKT); Progressive Knowledge Tracing (PKT).
	Predict the knowledge change, pass/fail predictions and scoring with game learning analytics and data mining techniques. Compare the accuracy ratio of tools in prediction.	Alnoso-Fernandez, (2019).	GLA; Hidden Markov Model (HMM).
	Estimate cognitive states and modeling learners' features and behaviors considering the forgetting behaviors.	Nagatani et al., (2019); F. Ma et al., (2024) ; S. Zhang et al., (2024).	DKT; Bayesian Knowledge Tracing (BKT), memory network, regression neural network, and Residual network; multi-layer context-aware deep knowledge tracking (MLC-DKT);
	Identify the relationship among the cognitive states, neural signals as well as objective behavioral readout such as response time.	Yousefi et al., (2019).	Neural encoder models involved GLM, Bayesian filters.

4.4.3 Learners’ Characteristics

Learners' characteristics, attributes, and personal traits are fundamental elements to the construction of user models and adaptive learning modalities. Analyzing these factors should favorize the evaluation of individual learning effects and feasibility, it requires the integration of perspectives of biology, physiological, psychological metrics, as well as, the construction underpinned by observations and assessments. This involves tracking and collecting data (e.g., learning trajectories, interactive patterns, learning preferences, mental states, motivation and metacognitive strategies). The integration of physiological, cognitive neuro, meta psychologically adaptive mechanisms into personalized deep learning models enables the interpretation and development of advanced, effective methods, tools, and technologies for adaptive learning programs to improve learning adaptability. Learner’ characteristics, epistemological foundations, meta-cognition regulations, meta-emotion management, and other meta-intelligent factors could explicitly and implicitly influence the development of learners’ meta-contexts, attention, execution functions, cognitive neuro adaptive mechanisms in acquiring knowledge components, as well as, meta-control, effective selection of personalized learning methods and activities. These features are reflected in individual cognitive levels, expectancy, interaction behaviors, mental states, skills types (e.g., routine expertise, adaptive expertise, innovation). All of these aspects can affect learners’ capabilities and self-efficacy in mastering higher-order thinking (e.g., abstract thinking, logical reasoning, analyzing, synthesis, evaluating, generalization, innovation). Learners’ cognitive (neural) executive functions, meta cognitive skills, assist them in effectively select and regulate learning strategies, so as to efficiently acquire domain-specific academic intelligence, general skills and individual-particular competence. Although adaptive learning technologies can automatically analyze and classify learners’ characteristics and skills to realize profile modeling, provide cognitive tutoring, learning feedbacks, emotional scaffoldings, metacognitive auxiliaries and interventions. Learners' traits, beliefs, and socio-cultural backgrounds may still affect knowledge acquisition, memory retention methods, acquisition of meta intelligence, learning adaptability. Learning hypotheses, personal epistemology, biases, emotional connections, and a sense of social responsibility can influence learners' brain and neuro activities in processing, selecting and optimizing learning. Learners can leverage cognitive preferences, executive functions, online metacognitive behaviors, offline metacognitive skills and so forth to engage in problem-solving, heuristic reflection, adaptive self-regulation, adaptive interaction and social sharing activities.

Intelligent tutoring and adaptive learning systems often adopt classical models for automated learner profiling, skills modeling, and adaptive learning activities. These embedded models may help reveal learner' effective interactive mode of learning, exercises, or practical works they have selected. However, the adoption of the single dimension of learning style scale has been questioned in terms of its logical feasibility in promoting meaningful learning. Contemporary reviews suggest that the use of integrated adaptive learning scales, models, and inventories, for assessing learner traits and improving learning performance, as well as, skill development. Current research indicates that the heterogeneity of target knowledge types (e.g., conceptual knowledge, declarative knowledge, procedural knowledge, conditional knowledge, and metacognitive knowledge) also determines the design of adaptive learning and cognitive systems. These advanced systems may aim to support personalized cognitive-neural activities and deep learning mechanisms.

4.4.3.1 Adaptive Cognitive Patterns/ Learning Modalities

Although a wide range of learning style scales are available for educators and adaptive learning designers to select and design appropriately the learning modalities depending on the contexts.

Learners' learning styles are still yet to be discovered by more underpinnings. Intelligent adaptive learning technologies that are based on appropriate learning theoretical models. It has the potential to identify learners' optimized learning, instruction, and evaluation by profiling or modeling techniques. Learning engagement, paths, and trajectories may reveal individual cognitive styles, thinking methods, and personal tactics. These data mining processes and learning analytics aim to model user profiles to provide adaptive parameters for stakeholders so as to increase learning performance, as well as, learning quality.

To a certain extent, learning style refers to a learner's needs and preferences for how to learn in specific circumstance. The classification of heterogeneous learning style scales relates to different theoretical foundations of learning. For instance, multiple intelligence theory classifies cognitive styles into information processing, perception, input and understanding including the following types: sensory, intuitive, visual, linguistic, active, reflective, sequential, and comprehensive. From the experiential learning theory, the learners' types can be divided into divergent, assimilated, aggregator, and conformed. Teachers or trainers may classify learners and select (personalized) adaptive learning modalities according to adaptable cognitive needs, knowledge objects, and learning activities.

Indeed, a learner's learning style and preferred cognitive patterns can be single-fixed or flexible adjustable. How effective adaptive learning activities can be selected suitably and sequenced optimally to an individual or a group may rely on attributes, learning needs, as well as, types and difficulty levels of learning tasks.

The results of literature reviews indicated that the applicability and popularity of heterogeneous learning style scales vary depending on the needs of specific learning contexts. The specific implementation goal is to obtain a preliminary user learning style by providing tests when users register and log into systems. Throughout the processes of monitoring, the learning performance such as behavior patterns, can be discovered in which case the style would be updated until it conforms to the individual needs. Eventually, the system may recommend precisely adaptive learning activities, sequences, learning resource media types, abstraction or concrete contexts within different levels of progress and learning needs. The activity sequence refers to the system recommending feasible learning plans based on user differences. The learning plan could include integrating learning objectives, tasks, operation steps, interactive forms, and evaluation mechanisms. The degree of abstraction of learning resources refers to what users used to describe the facts that they chose to learn, including structured knowledge or new concepts. Adaptive learning systems are able to adapt courses and learning paths to an individual' characteristics by integrating information and feedbacks about learner's learning preferences. The system updates the learning parameters in the user models according to the activity sequence, media type, abstract coefficient, learning times, actual learning time, pre-set time, until it meets the learning requirements of learners. Learning preferences could be detected and recognized by the behaviors, and provide adaptive learning paths so as to improve teaching and learning performance.

The table 6. below classifies the significant objectives, algorithms and tools in the predictive analytics of learning styles including profiling, adapt to personalized learning sequence activities and generate the recommendation.

Table 5. Analytics of learning style for curriculum sequencing, and learning path recommendation

Category	Objectives	References	Methods, Techniques
Analytics of Learning Styles	Recognize the students' styles; Detect and visualize the learning styles.	Liyanage et al., (2016); Wang et al., (2008); Zhang et al., (2021); Zhao et al., (2022); Yuvaraj et al., (2024).	NNs; GA; J48 DT, Visualization with group map; Style-based ant colony system; electroencephalogram (EEG); RF, K-nearest neighbor (KNN), multilayer perceptron (MLP).
	Discover learning styles of learners based on behavior	R. K. Jena, (2018);	R & R-Studio, classification accuracy

	change; Produce an adaptive supplementary learning path based on learning styles to increase (sustainable) effects and quality of learning.	Kuo et al., (2021); Bello Ahmad Muhammad, (2024) ; Xiao et al., (2024). 25/11/2024 21:23:00	(C4.5), precision, recall, kappa, ROC curve and F measure; Behavior analytics in LMS; Fuzzy C-means.
	Develop / implement (Felder–Silverman) learning style while taking into consideration learners' academic and personal information, feedbacks, preferences.	Bernard et al., (2017) ; Hussain et al., (2024).	ANN, GA, Ant colony, PSO; Clustering; Multi-layer topic modeling, fuzzy logic, Latent Dirichlet allocation (LDA).
	Increase the precision of automatic learning style identification.	Binh & Duy, (2017).	ANN.
	Measure the relationships between the learning styles and performance.	Gouripeddi & Gourripeddi, (2019); Lotsari et al., (2014); Weijers et al., (2024).	Association mining Apriori, K-means; SVM; Social network analysis, Text mining; LLMs baseline prompts, GPT-4.
Student profiling	Grouping or profiling of learners.	Minn et al., (2018); Lee et al.,(2012) ; Alvarez-Icaza et al., (2024).	RNN for DKT; Tag information, a time weighting factor, CF; OpenEdR4C.
	Measure similarities/differences among learners (e.g., attributes, abilities, interests), assign them into distinct groups, find the optimal pairs/groups.	Wang & Liao, (2011); Taniguchi et al., (2018); Pasina et al., (2019); Amiri et al., (2024).	ANN; Kolb inventory; Similarity coefficient matrix; Fuzzy Set Theory (FST).
	Characterize learners, construct the learner model.	Chaplot & Kim, (2017); Ning et al., (2017); Ma et al., (2023).	KT; LR, GB, DT, MF; Association rule and swarm intelligence.
Adaptive learning recommendation	Discover the optimal settings that enables learners to improve their learning capabilities, find the hidden patterns. Improve the efficiency of (personalized or collaborative) learning recommendation.	Dikker et al., (2017); Kausar et al., (2018); Troussas et al., (2023). 25/11/2024 21:23:00	EEG; GA; ANN and Weighted Sum Model (WSM).
	Improve prediction accuracy by minimizing the error in the prediction of test score; providing personalized learning materials.	Zhang et al., (2019); Madhavi et al., (2024).	MF applied in CF, GD.

4.4.4 Behaviors & Engagements

Learning Analytics (LA) and Educational Data Mining (EDM) techniques aim at predicting, analyzing of teaching and learning behaviors, emphasizing active engagement through interaction and collaboration among stakeholders. These techniques also focus on strategic design and formulation of contents, methodologies, and activities. The initiatives are to integrate cross-sectors efforts and contributions underpinned by interdisciplinary, with the aim to improve prediction accuracy, enhance teaching support, and offering practical guidance of interventions for educators. The objectives of analytics of users' behavior should facilitate improvement of interactions' quality and stakeholders' involvement in model construction. For instance, interpretating the relationship between engagement and performance; design tracking charts to visualize data and intuitively display learners' learning behaviors to instructors; exploring or predicting relationships between learners' online behaviors and achievements; analyzing how learning strategies influenced cognitive load, learning outcomes, and engagement; predicting and improving learning effect and collaborative learning outcomes, determining optimal pairs.

Learning interaction activities are a key part of tracking and evaluating learning behaviors that play an important role in data-driven autonomous learning and optimized learning in interactive learning environments. The studies indicated that the strongest predictors of online performance are engagement and motivation, educators and designers using decisions generated from motivational assessments and participation measures gleaned from learning analytics to tailor the design and the delivery of valuable courses. Behavioral and progressive data with relevant learning outcomes generated from quantity measurement and quality analysis of learning processes and interactive activities in different levels and dimensions. Learners' interaction with online learning activities and events include duration, response time of learners spent on learning tasks (Xion & Pardos, 2011), time spent working on an activity, interaction with videos, multiple-choice questions, summative assessment exercises, learners' views of a dashboard and information, weekly engagement in the activities, views of page, section and course, notes etc., The studies analyzed the characteristics of both the learning behaviors such as number of submissions, login times, frequency of viewing assignment etc., and the nonintellectual factors such as emotional states of e-learners as the main factors which influenced learners' achievements. Lu et al., (2018) collected data based on 21 variables consisting of behaviors surrounding video-watching, out-of-class practice, homework, quiz scores and that after-school tutoring that influenced academic performance.

The table below presents the objectives of the analytics of user behaviors including the tools and algorithms used, which gives an indication of the relationship between behaviors, strategies, actions, engagement and performance.

Table 6. Analytics of user behaviors

Category	Objectives	References	Methods, Techniques
Analytics of Users Behaviors	Design the trace charts to visualize the data and display students' learning behavior intuitively to instructors.	Wang et al., (2017).	LCA (Life Cycle Assessment) methodology, GBDT classifier.
	Provide the explanation of the interactions among the students and teachers on performance.	Agudo-Peregrina, (2012).	Agent-based classifications.
	Explore how the learning strategies of students influenced cognitive load, learning outcomes and engagement.	Kang et al., (2020) ; Huang et al., (2021).	Sequence clustering analysis; Clustering algorithms, coefficient analysis.
	Explore the relationships of or predict learners' behavior and achievements.	Umer et al., (2017); F. H. Wang, (2021).	DT- C4.5, Rep Tree, J48, KNN, NB, multi-layer perception (neural networks), sequential minimal optimization, latent semantic analysis, K-means, LR, RF, process mining; Multiple linear regression model.
	Predict students' engagement; evaluate the quality of interactions and students' involvement.	Ayouni et al., (2021); Mubarak, Cao, Zhang, et al., (2021).	ANN; RNN (Recurrent Neural Network).
	Predict the learning behavior features of students in MOOCs.	Cong Jin, (2020).	SVR.
	Predict and improve the learning effect and results of collaborative	Shin-ike & lima, (2009).	NN, GA.

	learning, determine the optimal student pairs.		

4.4.5 Emotional States, (Meta)Emotional Intelligence

Emotion analysis technology leverages social network analysis, text analysis, semantic analysis, facial expression recognition, eye tracking, posture, and voice to collect both explicit and implicit data types from learners (Ninaus et al., 2019; Dehbozorgi & Kunuku, 2024). Integrating the advantages that offered by advanced brain-inspired intelligence, cognitive neuro-computation, affective-socio computing, should enable educational and learning stakeholders to access and obtain more cognitive, neural, biological, psychological signals, and metacognitive feedbacks for enhancing cognitive processes, emotional regulation and improving learning experience. This multimodal, deeply personalized adaptive learning approach is expected to integrate methods, technologies, and tools to advance a new paradigm in adaptive education and learning effectiveness driven by generative AI, deep learning, brain-inspired meta cognitive neuro intelligence. Smart technologies contains well-being technologies, may adaptively employ instructional methods, conversational intelligent tutoring systems, personalized embodied learning companions, adaptive cognitive agents, empathetic emotional and metacognitive mentor to actively respond to learners' needs and enhance metaemotional intelligence (Lin & Li, 2023; Singh et al., 2023). In educational sciences of psychological development, cognitive neurosciences, psychometrics and cognitive neuro signals are crucial to explore how emotional components or elements influence learning performance, cognitive development, and behavioral changes through embodied cognitive agents, adaptive learning mediation technologies.

Reviews suggested that positive psychological traits, emotional management, and mindset adjustments should enhance knowledge acquisition processes, learning outcomes, and educational productivity (Singh et al., 2023). However, whether positive emotional factors can influence motivation, learning outcomes—such as interest, attitudes, cognitive change, and behavioral modification—remains uncertain and doubtful. This is because learning motivation includes components of expectation and value. When learners understand the meaning behind completing a task, learning behaviors and outcomes can be either enhanced or diminished. Although emotional agents may provide encouraging feedbacks and prompts when learners experience anxiety, frustration, or stress due to learning difficulties and failures. Nevertheless, evidence suggests that such feedback may lack logical feasibility in underpinning meaningful learning. Studies indicate that learners are more likely to improve learning and skill progression through the discovery of learning needs, un-mastery of knowledge types, or personal traits. Incremental guidance, tutoring, task-based learning, adaptive learning sequences, personalized remediation, empathetic learning companions, metacognitive scaffolding, and adaptive feedbacks, including neuro and bio feedbacks, have been shown to variously enhance and promote learners' fundamental cognitive functions, higher-order cognitive functions such as executive functions and metacognition, thereby improving academic and social intelligence.

Smart learning technologies, and brain-inspired intelligent adaptive mechanisms may improve learners’ understanding of their current cognitive strengths, interests, learning efficacy, as well as exploring weakness and potentials. Learning processes could be enhanced by cognitive, emotional, motivational and metacognitive neuro mechanisms. Therefore, designing adaptive learning mechanisms and intelligent environments should improve the acquisition of knowledge types and components, further influence performance, quality, and outcomes. These changes manifest through cognitive neuro functions such as attention, perception, and memory, as well as higher-order cognitive functions or executive functions (e.g., decision-making, critical thinking, problem-solving), metacognitive executive functions and adaptive neuro mechanisms (e.g., metacognitive monitoring and regulation), and metacognitive skills (e.g., self-regulation, adaptive interaction, and social-collaborative learning). Empathetic social intelligent learning companions typically encourage learners to engage in inquiry learning, dialogues, and gamified learning environments, for fostering sympathy, reflective interaction and socially sharing learning activities, which in turn promotes learning engagement, acquisition of academic intelligence and development of social intelligence (Taub & Azevedo, 2019; Taub et al., 2021; Alanazi et al., 2023).

The table below lists the objectives for the analytics of sentiments and emotional states, and the employed methods, tools and algorithms for evaluation based on the review of the literature.

Table 7. Analytics of sentiments and emotional states

Category	Objectives	References	Methods, Tools, Techniques
Sentiment and Emotional States Analytics	Recognize facial expression. Emotion prediction and regulation.	Hammoumi et al., (2018).	CNNs, Preprocessing, Feature Extraction, Classification.
	Sentiment analysis and classifications.	Mendoza-Palechor et al., (2019); F. Gkontzis et al., (2017); Jiang et al., (2015).	SVM, NB;
	Combine emotional learning analytics and educational data mining with the integration of methods from advanced learning science theories.	D'Mello, (2018).	Data-driven and Discovery-oriented analysis combined theories and science.
	Identify the impact of learning analytics interactive dashboard on user's emotional issues and self-regulation.	Zheng et al., (2021).	LA interactive dashboards
	Study how teachers interact with dashboard to understand self-regulation and emotional issues and create an emotionally adaptive learning environment.	Joseph-Richard et al.,(2021); Agustianto et al., (2016).	Viewing the emotional responses from learning analytics dashboards (PLA).
	Evaluate the emotional parameters that affect the employability.	Sharabiani et al., (2014).	Hierarchical Regression Analysis

4.4.6 Learning Environments Considering Technology Acceptance and Teaching Adaptability

Academic performance, learning styles, learning behaviors, and knowledge status, etc., are the fundamental adaptive parameters of developing adaptive learning analytics mechanisms and systems. The evaluation of learning risk is a prerequisite for improving user experience. User experience includes improving the system, technological adaptability, acceptance, emotion, attitudes, and learning difficulties, etc. A wide range of technologies have been adopted to identify and detect academic cooperation patterns or abnormal behaviors in different learning activities. The results of these processes can enable the learning system to take necessary measures and real-time responses or in-time actions. Classroom imbalance, student divisions, teaching system design, learners' emotions, attitudes and adaptability to technological characteristics may affect learning performance, quality, and lead to learning difficulties or increase the dropout rate. Therefore, it is necessary to analyze the specific reasons and solutions of learning difficulties and dropouts so as to provide academic support in solving this series of problems. The series of tools and techniques provide the support to reduce the occurrence of learning risks. In addition, the learning experience depends on the features of technology, the attitudes of human and their acceptance and adaptability. The research objectives are to provide personalized support service by big data, artificial intelligence, context recognition and emotional capture (M. Zhang & R. Zhang, 2020). This indicates the importance of sharing resources, domain models, the reusability and portability of the system, and the application of learning science theory relates to adaptive learning.

- The table below indicates the importance of the pedagogy support and learning experiences analytics including the technology adaptability and acceptance.

Table 8. Analytics of construction and impacts of learning environment and experience

Category	Objectives	References	Methods, Tools, Techniques
Pedagogy Support	Solve the problem of class imbalance, improve the student divisions. Curriculum analysis.	Shaleena & Paul, (2015a).	DT classification.
	Integrate the learning style scale and a more open learner model to provide personalized support services.	Cutad & D., (2019).	K Nearest Neighbor (K-NN).
	Provide support for solving the tedious work scheduling.	Zhang et al., (2020).	Mutation GA.

	Design interactive learning activities.	Chen et al., (2021).	Visualization and Content Analysis based on Cite Space.
Learning Impact, Technology acceptance	Measure learning impact based on the students' level of satisfaction.	Xiaona Xia, (2020).	Correlation Analysis
	Predict the student's attitudes of communication technology and mobile technology (ICTMT).	Verma et al., (2021).	Linear Regression Model (LRM).
	Predict graduation and enrollment.	Iatrellis et al., (2021).	RF models.

4.4.7 Learning Difficulties and Drop Out Prevention

In a formal e-learning context of contemporary education, academic well-being, learning difficulties and dropout have been considered as the main issues. Addressing the challenge of avoiding drop-out issues requires a comprehensive understanding of the underlying issues, effective planning strategies, prevention and intervention.

The approaches to model development for the early prediction of at-risk students indicated that a combined human-centric approach with the collaborative filtering, a recommender system and machine learning techniques including deep learning reinforcement, and artificial neural networks has always gained attention and can effectively facilitate decision making and timely planning for interventions. Although there are a variety of tools that can predict learners' dropout intentions, regardless of the teaching style or learning activities used in the course, there is still no consensus on the best way to understand the changing nature of this phenomenon. Simultaneously, maximizing the results obtained by predictions is a considerable challenge due to the large amount of data to select from. Learners' dropouts tend to be studied with different techniques and methods from multi-perspectives. The reasons behind the drop out includes socio-economic factors, personal traits, metacognitive strategies, motivational factors, emotional intelligence, resilience, behaviors, self-regulated strategies, teaching quality, constraints and conditions in the learning environments. Therefore, the more precise of indicators resulted in the more accurate of predictions, which could be realized by exploiting the available high-dimensional data jointly with machine learning techniques.

The table below lists the selected key studies of that review literature on analytics of learners with learning difficulties. It identifies the reasons and factors behind learning difficulties and the prevention of drop out, it also identifies the objectives and the modeling algorithms in the analytics of risks.

Table 9. Risks detection, prediction and prevention of learners in difficulties

Category	Objectives	References	Methods, Tools, Techniques
Risks Analytics, Model development, Solutions Building	Predicting students' risk of drop out through the insights obtained in enrollment, learning, retention and graduation.	Bukralia et al., (2014).	Boosted C5.0 DT.
	Detecting students at risk and adjusting profiles.	Lacave et al., (2017); Khan & Ahmed, (2020).	BNs; SVM, RF, NNs.
	Identifying students at risk in the exams.	F. Chen & Cui, (2020b).	Hybridized Deep Neural Network (DNN).
	Predicting students at risk-of drop out	Bañeres et al., (2020).	DT, NB, SVM, LR, KNN, Bayesian Additive Regressive Trees, Hierarchical Mixed Models, Neural Network.
	Building an early warning system.	Chung & Lee, (2018).	RF, boosted DT.
	Developing a solution to early prediction of at risk-students.	Queiroga et al., (2020).	Elitist GA.
	Helping to explain the reasons behind the drop out and amend learning behaviors.	Naranjo et al., (2021).	K-means, SVM.
	Developing drop out predictive models based on prototype.	Mduma & Kalegele & Machuve, (2019)	LR, multi-layer perception model, visualization model.
	Predicting at-risk students and providing measures for early intervention.	Waheed et al., (2020).	DANNs.

4.5 DISCUSSION

In this chapter, the methods for a critical synthesis of reviews in the emerging field of using learning analytics, machine learning, and big data mining are employed to construct a framework of precision adaptive deep learning. To date, grouping/profiling and prediction are the main analysis objectives. In short, most studies are selected based on heterogeneous data sources to provide a comprehensive picture of assessment. The results indicate that using an adaptive learning analytics approach is a rapidly-growing and high potential area to realize the construction of a hybrid flexible, customized, and personalized adaptive deeper learning ecosystem. The emerging issues/topics and future directions are discussed in the following paragraphs.

4.5.1 Precision Deep Learning for Individual Level

With social and technological developments, hybrid flexible and adaptive learning driven by learning analytics and big data mining has become an achievable paradigm for precise and refined education. Among potential methods to achieve precision and accuracy in education, Artificial Intelligence (AI) is considered one of the most promising means of technology-driven adaptive learning, which emphasizes the support of holographic data, the use of big data, machine, and deep learning methods are able to extract meaningful patterns and conduct personalized diagnostics, predictions, and prescriptive analyses. Accordingly, this review study shows that diagnosis and prediction are the most popular types of research, but evaluating experiments using data samples and dataset sizes, availability of technological resources and heterogeneous measurement environments tends to degrade the implementation of precision adaptive learning.

Therefore, it is necessary to combine user experience-based higher education management innovation data with contemporary AI adaptive sub-methods for unification (Zawacki-Richter et al., 2019). Although rapid advances in functional brain MRI, eye-tracking, facial expression recognition, and automated emotion detection technologies open up new potentials for monitoring learner' real-time cognitive states, and emotions (Ninaus et al., 2019) and providing immediate personalized feedback or recommendations. There remains insufficient research can provide precise and effective preventive, normative, and recommendatory measures that adapt to the individuals underpinned by a cognitive neuro-analysis. Emerging types of feedbacks or interventions are promoted in research projects to verify the feasibility of deep learning technologies in providing personalized assistance and accompaniment (Luan et al., 2020).

4.5.2 The Integration of Innovative Technologies and Learning Theories

Last but not least, the results found that most of these reviews selected features based on data availability and types of analytics. The adaptation is usually constructed based on the model's training and the performance in the interactive activities. A limited range of studies focusing on the value and viability of learning analytics on the detection of appropriate learning models to effectively enhance individual learning (Zhai et al., 2021). The advanced intelligent tutoring and adaptive learning systems should combine the capabilities of adaptivity and adaptability to facilitate adaptive self-directed learning, and collaborative learning (Dong et al., 2022). Depending on the heterogeneous needs and particular objectives, adaptive training and learning platforms, tools, methods and technologies can be designed on the use of theoretical foundations such as behaviorism, connectionism, connectivism, cognitive load, gestalt, constructivism, social cognitivism and meta-cognition (Kasabov, 2015; Chatwattana, 2018; Mavroudi et al., 2018; Xie et al., 2019; Schunk & DiBenedetto, 2020; Guo, 2022).

4.6 Conclusions and Recommendations for Future Research and Practical Work

Present studies results show that the analysis of cognitive processes, knowledge acquisition, didactic logic, and pedagogical features, which directly underpin quality of education. These learning and analytics models support the educational needs and learners' comprehensive skills development, enabling the adaptive learning systems design to be flexible agile, as well as to be personalized, thereby improving the feasibility of research and the accuracy of evaluation. Tracking and evaluation of learner’s learning should consider the reasons behind the learners' mistakes and their learning difficulties of which there could be many. Furthermore, the diversity of learning forms and analytics methods, and attractiveness of learning scenarios help to improve the learning effects and quality. For instance, peer assessment may facilitate knowledge acquisition methods among learners who possessed similar and different sets of skills, and improve the flexibility of the cognitive processes. Learning transfer can represent another form of knowledge transformation, learners may active current cognitive schemata and transfer learned experience to solve the problems in the other domains and contexts. Performance analytics is not only to improve learners' academic performance by increasing learning engagements or gains, but also to measure the significance and influences of evaluation indicators from a comprehensive perspective to develop a more refined education. To a certain degree, how learners’ motivation, negative emotion, and so forth, affect learning attention, enthusiasm and efficiency. Therefore, the goals of hybrid adaptive learning and training are not only developed for academic intelligence, but also for cultivating learners with the sense and awareness of cooperation, self-discipline, self-regulation, co-efficacy, for enhancing meta-cognitive abilities, meta-contextual intelligence, and meta-emotional intelligence.

CHAPTER 5. POJECT OF ET-LIOS

5.1 SUMMARY OF THE PROJECT IN THE CONTEXT

The objective of this project is to reflect the construction of adaptive learning by questioning the environment during the phases of design, implementation and evaluation. The other goals are to test their robustness when used in situ and to measure the learning impacts. Throughout the studies, this thesis work will make it possible to understand different aspects of learning, and to improve educational practices by relying on a solid body of knowledge.

This study specifically explores the conception of adaptive learning in the context of Education 4.0 paradigm and emerging trends under the vision of Education 5.0 paradigm in Society 5.0.

The work carried out in this thesis has contributed to construct an innovative adaptive learning environment to adapt to the differentiated needs of learners in order to achieve targeted educational objectives. The dedicated work in the design stage will make it possible to produce computer devices allowing the automatic capture of the traces of the learners.

In a second step, this thesis project will consist in studying the usage of didactic. The methodology proposed to assess the environmental impacts of innovative adaptive learning will be based on models, methods and tools for collecting digital traces to exploit and analyze learning scenarios. Thus, the qualitative and quantitative analyzes of the traces of the pupils (learning analytics), make it possible to detail the different strategies used in this educational environment and to generate patterns (Process Mining). The results of this thesis project envisaged will be a revealer of the functioning of the didactic system observed, and in particular of the differential forms which preside over the learning trajectories which might be singular.

5.2 DESCRIPTION OF THE SIGNIFICANCE OF THE THESIS

The main objective of the thesis project is to design an ecosystem model for adaptive learning environment, to analyze the stakeholders' coordination and involvement in the implementation of adaptive learning innovation. How educators or instructors can correctly select the appropriate strategies and customized methods of didactic transformation to enable learners to adapt to the individualized learning environment and develop their own abilities. The other significance of the thesis is to conduct the complement investigation on the triangular relationship of didactics, including the influencing roles and interplay between learners and educators, the epistemology, the dynamic knowledge transformation and cognitive changes in adaptive learning environment. Development of the didactic polyhedron model of adaptive learning and filling the research gap in current existing literatures.

5.3 PROJECT OF ET-LIOS

The new industrial revolution and digital transformation in the context of the COVID-19 epidemic is affecting all relevant sectors including higher education, research institutions, and this change is inevitable. According to the United Nations Industrial Development Organization (2021), the fourth industrial revolution is playing the key role in the digital innovation transformation of society. To accelerate the fourth industrial revolution and digital transformation by uniting global institutions to achieve inclusive and sustainable development. Therefore, global, national, and regional professional organizations, institutions, companies, communities, and associations play crucial roles in driving the new industrial revolution and digital transformation by uniting their expertise, collaboration, policies, and convening power. Higher education research is also constantly updating and reorienting the didactic sequences, reflecting on the impact of pedagogical innovations, promoting an attractive and valuable education better suited to the development of individuals and society, and their lifelong learning experiences.

Digital transformation is changing the content, tools and pedagogy of higher education. Digital transformation is changing the content, tools and pedagogy of higher education. Advanced development in algorithms, artificial intelligence and digital platforms are changing the respective roles of teachers and learners, as well as the development of training programs. To whom who and how do we identify the training content that best suits the needs? What will be the roles of teachers, trainers, researchers, practitioners and interdisciplinary learners in personalized digital journeys or digital learning communities?

The specificity of technical courses and the need to use machines and equipment's of an industrial nature make the issue of curriculum integration crucial and highly influential. ET-LIOS (Open License Technical Education for Competitive and Sustainable Industries of the Future), a project belonging to a sub-project of PIA3, which is led by the French National Institute under the Funding in Future Investment Program (reference number ANR-20-NCUN-009). PIA3 aims to economically strengthen the research and innovation efforts of the first two programs. PIA3 focuses on two vectors of economic and social transformation: the transition to a digital world and sustainable development. Through PIA3, the country invests in preparing for the future and supports the development of national initiatives that combine excellent research programs and innovative training. PIA3 funds facilities dedicated to basic research, supports devices directly related to the digital transition, and supports the advancement of teaching and research. Conduct research projects that expand educational innovation, integrate scientific and technological research into higher education, and open up new ways to manage and promote the development, demonstration and funding of innovative areas. Conducting experiments in the field of initial and continuing training, testing innovative training models, promoting innovative projects, and achieving results in the first cycle. Equity investments can enhance the involvement of education practitioners in the modernization of campuses or the provision of training services to the professionals. PIA 3 is organized around 3 priorities, including supporting the advancement of teaching; promoting research; and accelerating the modernization of organizations. The call for projects launched within the framework of PIA 3 will reflect the expectation to open new management methods for universities through the development of adaptive learning innovations; the expansion of research programs; the integration of research in higher education, and the promotion of new management methods to universities to support the progress of teaching and research.

ET-LIOS project involves stakeholders including teachers, trainers, educational innovation practitioners, learners, researchers, engineers and developers through joint collaborative actions through remote way to design protocols, and mobilize appropriate digital training resources and tools, and realize the blended synchronous and asynchronous learning through hybrid and flexible adaptive paths and supports. In future projects, we consider a paradigm transformation in the organization and practice of teaching and learning, incorporating youth empowerment to enable more learners to autonomously create learning spaces and flexibly regulate their learning patterns. Shifts in the engagement of ecosystem actors accelerate adaptive learning innovation researchers' fanciful or specious visions of the future. The abundance of massive open online course resources enhances the possibilities for automation and questions the contribution of face-to-face initial and continuing training and diplomas to each individual's career. In the context of the new industrial revolution and technology, what is innovative adaptive learning and training that can adapt to emerging jobs of the future of employment? How to employ it to cultivate the young generation with flexible learning adaptability and practical abilities?

The consortium of academic collectives from the scientific interest group S. mart brings together more than 80 universities, internal institutions and university components, public engineering schools or private schools. A project dedicated to higher education hybrid training for future industries. The goal is to bring together the experience and evidence of the continuity of distance learning and training acquired by the member institutions of GIS S. mart in the fields of technology and science during the Covid-19. Within a period of 18-months, ET-LIOS aims to deliver, measure and facilitate the open shared educational contents for the future industry around four hybrid education sub-projects involving IT infrastructure of virtualized, shared software resources, supported and managed by regional centers, and supporting the implementation of different educational modules. Development of an open, shared digital infrastructure to ensure the virtualization and hosting of educational content through the software solutions, including educational platforms and applications; building, developing and deploying educational content; measuring program performance and impact on targeted training; and disseminating and delivering educational content.

The production of the entire pedagogical innovation project required the expertise and experimentation of S. mart community members. The development and soundness of the content, variation, and portability of the innovative materials through proof of concept (from the Covid-19 era or benefiting from previous GIS projects) provided to the entire educational community and S. mart education experts required a larger educational scale. The expertise and protocols of S. mart community members helped to significantly contribute to the success of the school year and performance.

As a sub-project of pedagogical convergence, ET-LIOS project aims to address the future of competitive and sustainable industries and includes six modules such as design-simulation - 3D prototyping; advanced manufacturing and metrology; cyber-physical production and e-maintenance system; digital twin and virtual commissioning for automated production; intelligent systems and multi-physics modeling; responsible and sustainable engineering. The GIS S.mart[6] consists of 10 regional centers, managed by universities or engineering colleges and related institutions, whose purpose is to bring together teaching or scientific expertise, technology platforms and software resources to support higher education training missions, technical research efforts and industry partnerships. Offers bachelor's degree programs of a scientific and technical nature including licenses in science for engineers, EEA, Professional licenses in subject, Diploma university of technology such as "mechanical engineering production", "industrial computer electrical engineering", "Industrial engineering and maintenance", "quality, logistics, industrial and organization", "physical measurements", "material science and engineering", "Packaging, wrapping and conditioning", Related professional licenses, INSA, Polytech, UT's comprehensive preparation cycle and engineering training.

Educational project management activities including planning and monitoring of projects; animation of project meetings; creation of deliverables; information and document management. The work of maintaining the necessary activities for learners and teachers, has 3 educational stages of tasks: firstly the remote, initial activities for initiation, discovery or preparation, then in situ or on-site access and basic technical means of implementing resources and training courses, and finally, comprehensive and reinstate the sequences in which the skills learned were taught. Didactic engineering and communication activities including gathering training needs for teaching teams and laboratories; defining educational scenarios to be implemented; producing educational

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[6] https://s-mart.fr The GIS S.mart offers bachelor's degree programs of a scientific and technical nature including licenses in science for engineers, EEA, Professional licenses in subject, Diploma university of technology such as "mechanical engineering production", "industrial computer electrical engineering", "Industrial engineering and maintenance", "quality, logistics, industrial and organization", "physical measurements", "material science and engineering", "Packaging, wrapping and conditioning", Related professional licenses, INSA, Polytech, UT's comprehensive preparation cycle and engineering training, etc. Educational project management activities including planning and monitoring of projects; animation of project meetings; creation of deliverables; information and document management.

materials for various work situations determined in consultation with teachers; setting up video systems that can remotely track platforms and track progress of scenarios; define methods of assessing students in different work situations; participate in the development of dissemination locally and through the Internet.

GIS S.mart community is created to ensure the training of learners in the theme of future industry through an intelligent professional network. This program is supported by GIS S.mart, which is responsible for coordinating national-level activities between regional centers and related institutions. The social sharing of pooled resources and expertise enables the community to organize frequent thematic training and dissemination meetings under the leadership of the integrated management, bringing together the experience gained during COVID-19 in the continuity of distance learning and training, developing blended modules that also meet the needs of "autonomous learning", "flipped classrooms" and other innovative training methods.

To promote learners' autonomy and verify the effects of innovative learning, ET-LIOS project aims to develop the protocols in experiments, and combines the shareable, compatible, scalable resources to be available to the stakeholders and academic alliances including S.mart members, practitioners and learning participants. The integration of blended learning platforms and innovative didactic resources that are compatible, accessible, controllable, adjustable, which make possible of collecting real-time data remotely. It allows the collaborative and coordinated work among participants involve in different institutions to promote the adaptation of the target courses and training modules. For example, instead of providing the learners with the direct responses and corrective work through the agent or human tutor or peers in traditional learning environment, learners self-regulate the learning with the hints and feedback to develop correct and more new possible solutions. Learners can use the simulation software like a video game in an interesting environment. The pedagogical agent tools provided facilitate higher-order thinking and cognitive process, especially online validation of the effects of the learner's learning through measuring the performance and impact on the target training.

This study integrates the evidences of Module D in ET-LIOS project in implementing digital transformation and innovation. The main objectives are to design an adaptive learning ecosystem model through the completion of the research gap, analyze the coordination and cooperation of stakeholders in the implementation of pedagogical innovation, and how educators can properly select appropriate instructional content delivery strategies and methods to achieve learning innovation.

Serious Games Research Laboratory (SGRL[7]) has piloted and produced several projects as a university research group, such as Mecagenius (learning mechanical engineering), Cell Cycle Learn (learning the cell cycle) or 3D Virtual Operating Room (collaboration and communication in the operating room). In addition to its competences in designing and development of serious games, SGRL also has expertise in evaluating learning and training tools. These evaluations allow for "business software" readability in terms of usability and educational benefit, keeping the learner's learning trajectory coherent. As part of this project, it seemed important for us to be able to draw lessons from these areas of digital training course mobilization and to provide indicators about the quality and effectiveness of the technology training courses.

5.4 Experimental Pocedure

This research project contributed to the proposal of a viable training program through the Joint Action for Pedagogical Innovation. Figure 5 present the protocol constructed, system developed and evaluation deployed in ET-LIOS project. In the initial stages of implementation, the

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[7] Pluridisciplinarity Research Group - INU Champollion – Albi - France : *https://www.univ-jfc.fr/grp/serious-game-research-lab-sgrl*

integration and sharing of experiences of Smart community members is beneficial to promote higher-quality implementation. In the initial phase of the project, the pedagogical innovation practitioner-led stakeholder group included developers and engineers working together around a mutually agreed protocol to improve the design of UI and UX for the software system. During the implementation phase, developers and engineers worked together to develop a learning companion software based on testing and deployment.

As part of the research activities, serious game research lab is involved in the development of automatic assessment and feedback tool embedded into learning software Connect I/O for allowing the teachers to avoid repetitive correcting work and learners to do practical work more effectively. With these tools, learners can conduct their work in application and receive corrective hints and feedback. The tools provided facilitate learning and analytics, especially the online validation of the effectiveness of the actions taken and performance measured.

Learner behavior data were tracked, collected, recorded, and sent to a server to provide the basis for learning analytics. Learning analytics may integrate with cognitive psychometrics, pedagogy, cognitive science, and brain science to design adaptive learning systems. These system technologies may combine with algorithms, artificial intelligence, machine learning, deep learning, and natural language processing for effective personalized automated feedback and adaptive intervention according to the contextual needs.

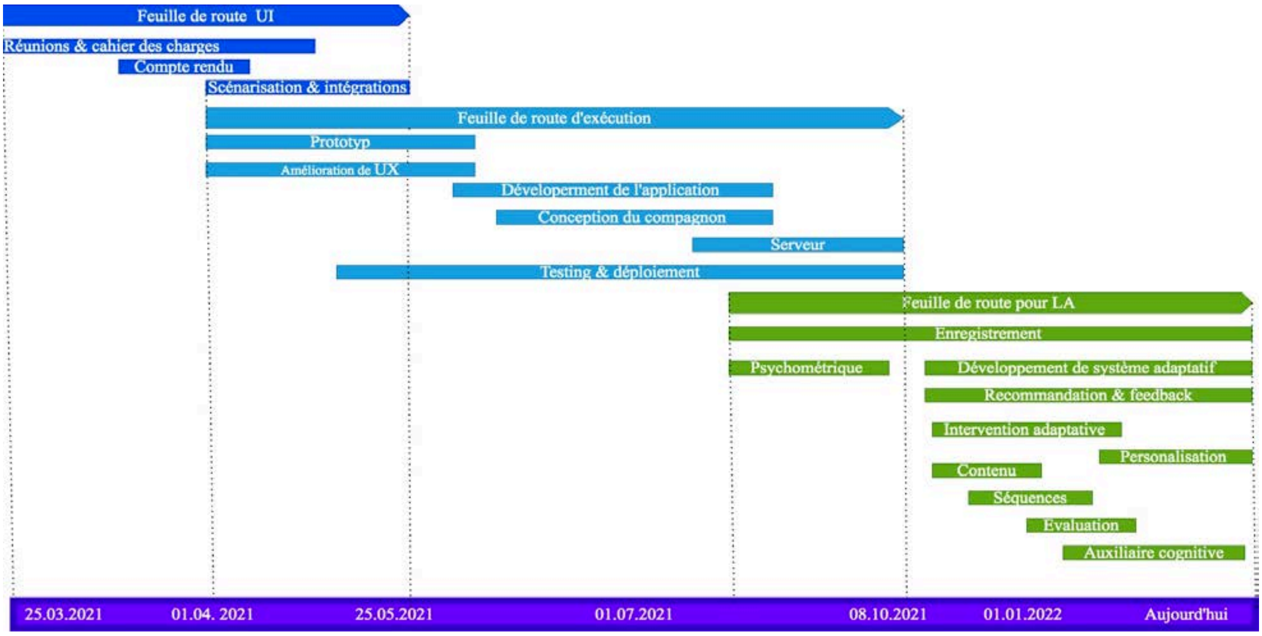


Figure 4. Protocol, implementation and evaluation in ET-LIOS project

5.5 Adaptive learning system framework

Learning and teaching impacts can be measured and evaluated based on multi-dimensional variables and indicators: learner aspects include measuring learning time, learning performance, attendance, engagement, learning risks, learning strategies, motivation, persistence, etc., and software evaluation includes utility, usability, accessibility, effects, attractiveness etc.

The objective of this work is twofold. On the one hand, to provide a common reference framework that allows the assessment of all these initiatives, despite their different nature, through objective and comparable criteria; on the other hand, to provide support in the production of case-by-case assessment tools, taking into account the specific nature of each resource. The project will support quantitative methods by implementing steganographic assessment through the collection and analysis of user traces in possible cases (e.g., virtual labs, interactive digital events, etc.). In the other hand, a qualitative analysis framework will be proposed, in addition to activities to collect the data needed for the assessment, with the aim of understanding and mastering the technology in a competitive and sustainable way. The purpose of impact measurement is to measure the performance and impact in the context of training. More specifically, measuring impact means measuring the effects on learners' adaptive capability to the new course materials delivered as part of blended learning instruction. These consequences can be psychological, social or even impact learning. For this reason, we have worked with various partner universities to develop interactive course materials that respect the constraints associated with the content of each module and the protocols established by the instructors. These devices are "instrumented" so that they can automatically track indicators each time they are used. Thus, the measurements taken ensure the quality of the support and activities provided, and identify areas for improvement.

The first application capable of correcting learners' work and providing them with personalized feedback has been implemented. It allows the human tutor to better follow up on this feedback, while the learners can try as many times as they wish and learn from the success and mistakes, while focusing on the instructions provided by the digital companion integrated into the activity. Another application allows the learner to assume the role of corrector by evaluating the work of his peer, whose own work is also evaluated by them. This process, called peer evaluation/assessment, allows learners to learn from their own mistakes as well as those of others. Once their work and corrections are completed, learners move on to the self-correction phase where they can revise their proposals taking into account their peers' comments.

Adaptive learning and intelligent tutoring systems take into account expert/ domain knowledge, didactic models, and learner models in order to support the construction of adaptation models.

Learning analytics collects, tracks, and measures learning progress, combined with data mining techniques such as machine learning to reinforce intelligent diagnosis and adaptive learning. The formative evaluation and feedback provide different types of adaptive solutions such as adaptive content presentation, intelligent tutoring, learning sequences, guidance, navigation, conversation, assessment, etc., Open learner models could be constructed to support more personalized learning. An integration of personalized adaptive learning analytics models, and meta-cognitive auxiliary models into the open learner models could favor personalized deep learning.

The contribution of this investigation is threefold. First, a generic meta-cognitive adaptive framework aimed at enhancing personalized deep learning is proposed. Second, some(a) specific approaches to adaptivity based on learning measurement are (put forward) reflected within the framework. Third, the framework was validated and the approach was evaluated in order to determine their effectiveness in learning provision in an adaptive learning analytics system.

An experiment conducted with 50 participants produced positive results. They indicate that adapting learning analytics according to personalized automatic evaluation and formative feedback yields significantly better learning outcomes and learner satisfaction than without personalization (adaptation).

5.5.1 The Reflection of AI-Empowered Adaptive Learning Environment Framework

A generic framework is depicted in figure 6. It presents how a personalized adaptive learning can be enhanced through intelligent, adaptive and deep learning systems as well as feedback loops. Adaptive learning design, methods and techniques are elaborated in the following paragraphs.

Firstly, a classical didactic engineering in adaptive learning involves the pedagogical innovation through artificial intelligent techniques. The general components of an intelligent tutoring system (ITS) contain the domain knowledge model, the learner model, and the pedagogical model. They respectively solve the issues of what to teach, who to teach, and how to teach. AI-enabled ITS can mainly provide adaptive support along five main dimensions: (1) being able to automatically response inquires, provides hints, remedies, and suggestions for learners in problem-solving processes. (2) being able to record the learning trajectories, represent the knowledge construction processes, dynamically update the models, and provide the feedback for learning design. (3) being able to describe and evaluate learners' learning performance and impacts, and predict both learning gains and learning difficulties from the behavior and the engagement. (4) being able to give semi-dynamic or real-time feedback, provide targeted learning solutions, suggestions, and recommend learning resources, learning paths or partners. (5) being able to interact with users to obtain multimodal datasets, to perceive, detect, regulate and predict learning interests, emotions, motivation and metacognition based on deep learning techniques and neuron models. Intelligent learning system supports teaching that is improved mainly through automated profiling of learner profile, updating of knowledge graph, sequencing of curriculum, adjusting of learning tasks, and building of smart credit tables. Adaptive learning system supports personalized learning experience and explicit feedback loop. This support is provided using intelligent learning environment construction, learners' profiling, and multimodal diagnosis, prediction, reasoning, assessment, prescription and recommendation. Adaptable learning system is able to provide step-by-step adaptation, dialogue based-reinforced deep learning, exploratory learning, personalized learning assessment. Adaptive learning system originates in learning management system. General architecture of adaptive learning system often adds extra models: an adaptation engine and a user interface. The adaptive learning engine is able to generate appropriate learning content, customized activities that derived from learner's personal traits and specific circumstances. It empowers user-centered personalized tasks, learning paths, scaffolds and adaptive interactions. During the collection of behavioral data, learner's achievements and knowledge levels are classified, and their learning interests, preferences, cognitive styles, metacognitive strategies are analyzed and predicted. Personalized adaptive learning is able to underpin precise learning and cognitive maps construction. All to provide implicit feedback, reflective assessments and companionship services to encounter individual learning and developmental needs. Moreover, metacognition intervention and auxiliary mechanisms allow users to develop self-regulation, and socially-shared learning skills from more open hybrid flexible learning environments.

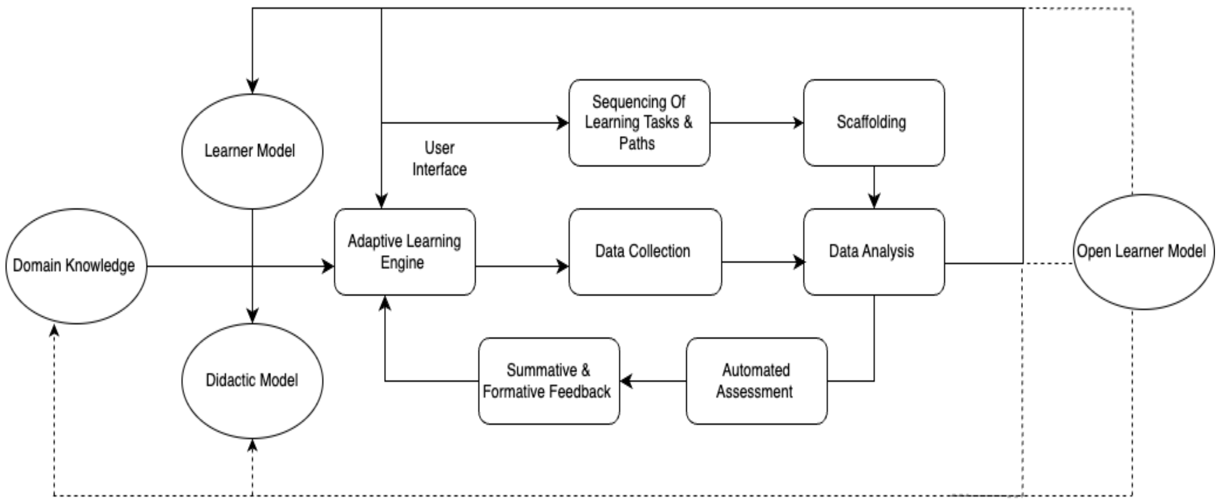


Figure 5. Personalized and automated feedback loop

5.5.2 Learner Model and Modelling Techniques

A wide variety of learner variable characteristics, such as learning needs, levels of knowledge, cognitive status, emotional state, motivation, meta-cognitive strategies, and learning preferences can be integrated into the learner model. The proposed framework supports both static and dynamic learner modeling based on explicit, implicit, or hybrid feedback.

The classic learner (knowledge) profile modeling and assessment techniques such as overlay model, buggy/faut model, stereotype model, Bayesian network model. Bayesian related machine learning analytics techniques allow the construction of multimodal adaptive learning. The feedback includes explicit and implicit or a hybrid method. For instance, INSPIRE is the system applied explicit learner feedback, which used a questionnaire to identify individuals' learning styles. Protus system, which used implicit learner feedback (in the form of page visits) to construct learner models. The example of the system that employed a hybrid method of learner feedback. For instance, the Oscar CITS (conversational intelligent tutoring system) employed static models in which learners completed a questionnaire to identify the learning styles at the initial interaction stage of learning; the learning styles information was stored in their model and kept modified under the dynamic interactive data modeling for the support of adaptation.

Certain computer-assisted instructional systems (CAI, although often under another name, e.g., adaptive educational hypermedia) effectively employed a number of domain and pedagogical models: knowledge of what is to be learned and knowledge of how to teach it (e.g., whether to use linear or branching procedures). The fact that many ITSs contain a great deal of learner-related learning and knowledge acquisition experience, e.g., learners' interactions with the system, the difficulty level of learning material to the learners, their misconceptions, cognition, motivation, emotional states and metacognition when using the system.

All this learner feedback and informational knowledge can reflect what and how it is being taught, as well as what support needs to be provided, when, and from which targeting. Indeed, ITS can be developed in more advanced forms. For example, HAITLS or hyper hybrid AI tutoring learning systems. By combining information from all the learners who have interacted with the system, ITS can enhance the learner model, from which the system can learn to predict what pedagogical approach and domain knowledge is appropriate for a target learner in a specific context, scenario, goal, stage, or situation. The learner model allows automatic assessment, intelligent diagnostics and tutoring system to recommend and adapt, machine learning enables the adaptation particularly accuracy and strongly powerful.

5.5.3 Domain Model

The domain model may contain the learning resources, instructional material, learning objects or exercise paths of any domain knowledge. Different representations, such as map, network, and hierarchy models can also be used. The content of the domain model may be classified and annotated to facilitate the retrieval of learning resources and to support adaptation.

The domains of adaptive learning systems are usually related to STEAM subjects such as science, technology, engineering, physics, language, management, and mathematics topics are all the major adaptive purposes of intelligent tutoring systems. However, the domain knowledge model in the proposed framework is flexible in terms of the scope of content, levels of knowledge, preferred representation, and management.

5.5.4 Didactic Model

ITS pedagogical models represent the knowledge of effective methods of teaching and learning gained through the research of interdisciplinary teams such as engineers of pedagogy, didactics, teaching specialists, and learning scientists (although it should be recognized that some ITS developers incorrectly believe that they have sufficient pedagogical expertise). The pedagogical knowledge that has been presented in many ITS systems includes knowledge of pedagogy, zone of proximal development, cross-practice, cognitive load, and formative feedback. For example, the implementation of Vygotsky's "zone of proximal development" model of pedagogy ensures that the system provides learners with activities that are neither too easy nor too difficult, while a model that implements personalized formative feedback ensures that feedback is provided whenever possible to support individual learning.

As the target learner performs the learning activities that the system interacts with and selects, the system collects data that characterizes the individual human-computer interactions and collaborative behaviors. How learner's learning curve, level of completion, engagement, errors of fact, reasoning, physiological and psycho-brain cognitive activities affect emotions and performance. These variables have become important factors in influencing adjustment of didactics.

Data analytics may combine human judgment and automated assessment, both of which can provide learners with personalized formative feedback (based on individual responses and needs to support learning). In parallel, updating pedagogy models and learner models is based on providing evidence to inform the system's decisions about which following adaptive activities and content should be provided, informing educators in redesigning and updating domain knowledge segments, expanding and supplementing expert models. At the same time, it serves to optimize the learning and management models to all users.

The AITS Learning Assessment and Feedback Loop was based on 1. the use of domain, pedagogy, and learner models to provide adaptive learning activities. 2. data collection and analysis (formative or summative assessment). 3. updating relevant model adaptation methods, techniques, and tools.

This loop means that learners will construct their own unique learning paths through learning engagement and interaction. Learner adaptability is reflected in a resourceful, agile, and versatile system. The amount of time a learner spends on a task may vary depending on how difficult, challenging, and interesting the material is. When learners make fewer attempts, they are likely to understand concepts and reduce learning activities. When learners fail more often or make more errors, the majority of the active and motivated group may seek help, resources, guidance, and questions to achieve the learning objective. The type of interaction a learner chooses may reflect their learning preferences or adaptive cognitive style.

Learners learn by exploration, discovery, and improving their learning through cognitive activities such as dialogue, moderation, and navigational recommendations. However, this does not mean that learners' learning is optimized. Therefore, the increase of metacognitive aids and intervention models, such as the open learner model, allows learners to reflect on and evaluate the selection of adaptive strategies.

Open learner models are often available through tools such as learning analytics dashboards, and progress bars. The purpose of openness is to allow learners and teachers to visually and clearly examine and reflect on the teaching and learning activities that have taken place as well as the system's decision-making adaptations. Learners may self- regulate their progresses, completion, repetitive errors, allowing teachers to capture learner performance in the overall learning environment, knowledge acquisition, misunderstandings, learning curves, and strategies as they occur, and providing teachers with evidence to reflect on adaptive design.

The open learning model supports metacognitive activities and self-regulatory activities based on self-efficacy. The social open learner model allows for adaptive collaboration, adaptive assessment, peer learning and assessment, social comparison, gamified competition, and cooperation.

5.5.5 Intelligent/(Auto)Adaptive Model/Mechanism

Adaptive methods include adaptivity, adaptability, intelligent adaptability, and hybrid flexible adaptation. The construction method, principles of selection, and implementation of the adaptation model depend on the knowledge, didactics, management, and learning target requirements. An adaptive method is driven by knowledge goals. For example, didactic practitioners may develop an adaptive model based on subject knowledge types, goals, and objectives. The model contains knowledge types and number of purposes, and difficulty levels. Educational or instructional practitioners have experience in designing different amounts and levels of learning content, learning materials, and learning activities into adaptive systems. The integration of knowledge mapping, pedagogy, and learner profiles allows adaptive learning mechanisms to sequence and present knowledge according to the type of goal, recommending adaptive cognitive, perceptual input, processing and comprehension strategies, and media resources.

Instructionally-led adaptive modeling is based on three main approaches. The adaptation can be based on traditional pedagogical methods, principles of learning science theory, artificial intelligence, machine learning, and deep learning techniques, or hybrid adaptation techniques. Contemporary adaptive approaches tend to blend multiple models for adaptation according to context and stakeholder needs.

Mathia is an intelligent adaptation model/mechanism/device guided by behaviorism. It may be used to understand learning progress based on successes and misunderstandings by monitoring the learner's learning behavioral processes based on the learner's history of adaptive learning interactions. Providing (automated) assessment, revealing learner errors, and navigating personalized learning paths. Alta is an adaptive model of intelligence based on the principles of cognitivism, whereby learning materials, activities, and sequences are tailored to the level of knowledge of the learner according to the learner's progress, i.e., cognitive level. Beginner, Intermediate, Advanced, Uncertain, and Difficult learners often receive different amount of feedback on the content, paths, and programs, and the learners can choose the curriculum, learning, and sequencing of exercises based on the optimal and proximal zone of developmental. Item Response Theory, Benchmarking is often used in adaptive testing techniques to test learners' level of competence to tailor remediation, referral, and counseling. Cognitivist-centered adaptive models emphasize the application of dual channels, cognitive flexibility theory, cognitive load, working memory, long-term memory, and metacognitive principles to design tutorial instructions and sequential learning scaffolds and micro-learning tasks.

Furthermore, learning theories such as Gestalt, Constructivism, Connectionism, and Connectivism have different implications for constructing adaptive models in different contexts to facilitate knowledge change and learning experiences.

Intelligent adaptive tutoring system that is based on Socratic dialogue. CIRCSM is a typical intelligent tutoring system. Multi-agent intelligent learning and tutoring systems may be based on a blend of different learning and teaching principles, natural language processing, and generative technologies that explore the learner's cognitive level, knowledge acquisition, learning behaviors, and emotional responses in dialogue. Intelligent tutoring systems and devices that are based on embodied cognitive virtual reality, augmented reality, and mixed reality immersive experiences help learners reinforce the experiential cycle of deep learning in embodied contexts.

The agent-based system can provide one-to-one instruction, corrective feedback, remediation, demonstration, and other coaching and interventions based on perception. It can be applied at all stages of learning for different knowledge types, objectives, and learning audiences and provides real-time dynamic feedback to teachers, learners, administrators, and other instructional or pedagogical innovation teams.

An adaptive and adaptable model centered on the learner's learning goals. It is based on the principles of cognitive neuropsychology, brain science, and learning science. The model is designed to observe, measure, and assess learners' attributes, learning history, interests, preferences, motivation, perceptions, metacognitive strategies, and abilities to formulate learning goals that meet the learner's expectations and improve the learning experience. The model focuses on the application of empiricism and humanism, and it emphasizes self-regulation, self-efficacy, self-assessment, self-directed and meaning-constructive learning.

Learners develop their own adaptive learning and interaction strategies based on self-reporting methods, learning analytics dashboards, and open learning models. This approach is based on the learner's perspective and it facilitates the development of the learner's attitudes, beliefs, mindset, thinking, and personality, thereby promoting their deeper memory, learning buoyancy, and psychological resilience. The protege effect and Kohler effect imply that adaptive peer learning is based on the understanding that the learner's own motivation, effort, and ability level can influence the overall outcome in order to optimize learning. Learners can develop flexible adaptive skills by encouraging self-teaching, teaching others, peer learning, peer assessment, and teamwork. Indeed, the Kohler motivational gain effect applies to both simple and complex problems and tasks in the short and long term.

The goals of the adaptive model built from the management aspect include building learning communication, feedback, early warning, and intervention mechanisms based on education, pedagogical instruction, didactic curriculum, and classroom goals. Adaptation model based on ITS+ to build learning ecosystems, smart campuses, and ubiquitous mobile flipped classrooms for synchronous and asynchronous learning management. The establishment of these management mechanisms may be based on the macro, micro, subjective, or objective needs of the learning management system. Thus, the objective determines the source, type, and purpose of data collection, the application goals of learning analytics, and the scenarios for intelligent adaptation. The establishment of multi-modal data types contributes to comprehensive dimensions, recommendations, feedback, early warning, intervention, and assistance in learning progress.

This improvement is based on the needs of individuals, organizations, and even societies to help achieve static and dynamic small and large-scale adaptation from both short and long term. The goal of this research project is threefold, namely that the educational management goal is to improve teaching impact, attraction, sense of added value, engagement, and academic performance. Educational goals are to improve the learning experience, engagement and success rate. Curriculum goals are to improve course grades and the possibility of expertise integration.

Classroom goals such as knowledge point mastery, cognitive measurement, mental efforts, and adjusting the levels and sequences of material content (Guo, 2022). This adaptation model integrated multi-objective and multi- interaction datasets of learners' profiles for adaptive mechanisms, feasible implementation, and sustainable impact in the architecture of hybrid agile system.

5.6 FRAMEWORK IMPLEMENTATION

In this section, a specific approach to adaptivity is proposed as a method of validating the framework. In order to measure the impacts, an adaptive learning analytics tool is implemented within the framework.

The adaptive system includes three components: a domain model that constructs and reorganizes a network of knowledge points and adjusts practical schema/ learning paths. A didactic model that integrated the didactic methods into pedagogical activities, instructional design, and curriculum redesign based on learning analytics. A learner model that tracks the learning progress and monitors the learning behavior. A personalized formative feedback model/tool to support the adaptive instruction such as hints, corrections, and remedies in order to facilitate learning. Adaptive learning analytics under a standard package SCORM implements a restricted version of the feedback model in order to adapt the learning needs and experience of specific practical works. The objective is to conduct the predetermined protocol in a reflective experiment. The learner model contains the basic learner's profiles, learning history, and progress. It is constructed mainly for the adaptation of knowledge mastery and learning experience, whereas the domain model contains instructional material related to the subject of mathematics for computer science (logical combination). In this approach, all learners do the same practical work and they are able to choose a different practice sequence. The automatic evaluation and formative feedback model constructed personalized hints for each learner by analyzing learning successes and mistakes.

The approach describes cognitive process, learning behavior, and knowledge change, predicts learning success and mastery, diagnoses difficulty levels of practices according to the domain model, learner model, and prescribes personalized hints that correspond to specific cognitive status.

The components of the adaptive learning analytics system and the relevant reflection of construction and impacts are described below.

5.6.1 Learner Model

The learner model consists of a representation of the assumed, analyzed, and assessed state of the learner's knowledge. The learner model contains a large amount of interactive information and knowledge generated by the learner through the learning activities and practice paths. The presentation of this information and knowledge facilitates the demonstration of common errors made by the learner, the inference of unmastered knowledge structure, the prediction of the probability of mastery through successful practice attempts, and practice strategies that reflect the learner's engagement, persistence, motivation, and likely state of mind and emotions. The learner model showed what was being or had been taught, and how learning was taking happened.

Teachers combined all the information about learner-system interactions to update and determine what can be challenging for the learners, redesigned lessons content and characterized knowledge structures, planed effective teaching and learning activities, and optimized machine learning methods, techniques, and tools. As a result, pedagogical models can be updated and improved to influence the implementation of adaptive mechanisms and methods. The goal of enhancing learner models with machine learning technologies as instructional tools is to further adapt adaptive mechanisms to reflect what automated assessment and feedback content supports, when it facilitates learning, and how it can be personalized to target learners at a particular stage. Future projects will consider iterative algorithmic upgrades, extensions, and additions to the learner model.

5.6.2 Domain Knowledge Model

The traditional domain knowledge model is based on either a hierarchical or a network-based representation. With the revolution of industry, the specific skills required and the workforce demanded in the future may differ from the present society.

The current domain knowledge model is based on the proposition of hybridization of automatic control practical courses and its relevant learning resources to be adapted to learning objectives that are linked to the curriculum and learner's level. It involved complex problem-solving skills requiring multidisciplinary knowledge, spanning from mathematics and physics to computer science and logic programming while including sensors, actuators, and electrical and mechanical engineering. Domain knowledge allows the mechanism to bridge theory and practice in industrial control and automation training. It requires the transfer of knowledge and know-how to learners. The courses are usually divided into theoretical (lectures), exercises (tutorials), and practices (practical works). The training courses required learners/students to equip an interdisciplinary procedural knowledge so as to master the applied transdisciplinary knowledge and approach that was coupled with practical work skills, project and problem-based learning (abilities) in the virtual learning environment.

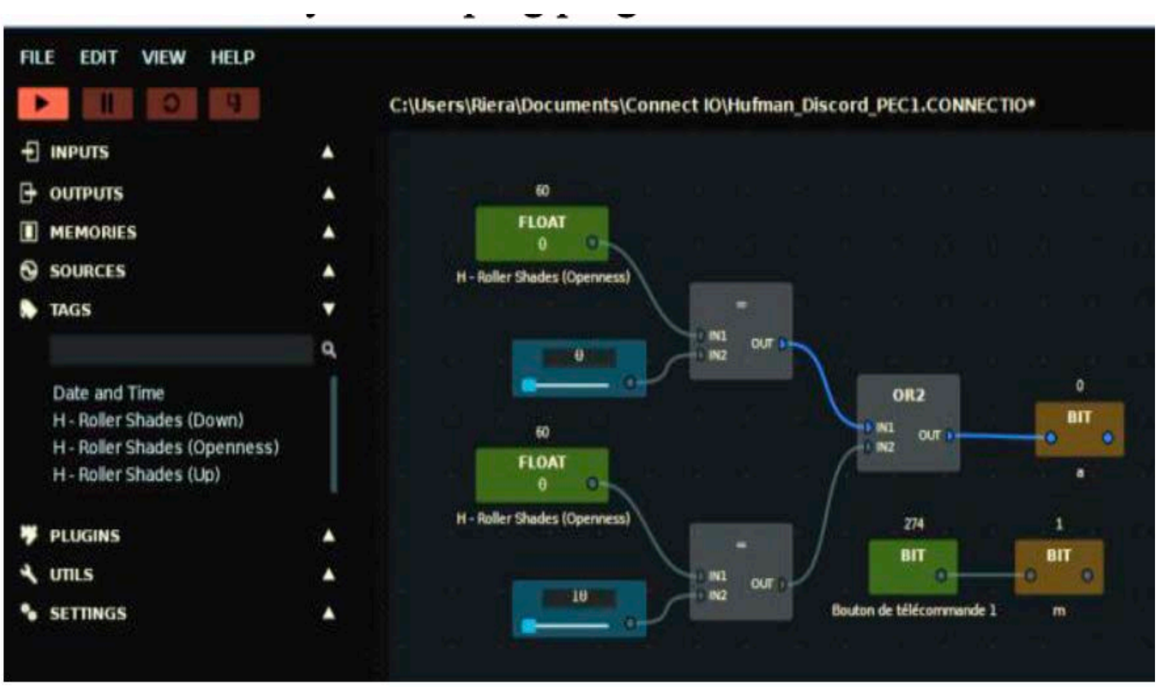


Figure 6. Practical learning schema work in logical combination course

5.6.3 Didactic Model

The pedagogy model integrates knowledge of pedagogical theories, learning science theories, and design principles used in the study of effective instructional delivery, coaching, and learning.

This knowledge involves teachers working with system developers, machine learning engineers, pedagogical, instructional engineers, and learning innovation researchers to develop feasible meaningful learning and cognitive activities.

This classroom training approach involves applying the pedagogical foundations of practical work. Small-step learning based on trial-and-error successes and failures allows learners to reflect on their strengths and areas for improvement. Based on a summative analysis of the different theoretical foundations, the design principles of the methodology should be guided by how to effectively instruct and provide feedback to support learning. For example, explaining the benefits of success and failure in trial-and-error exercises will help developers to better design pathways and feedback programs that promote optimal learning.

5.6.4 Formative Automatic Feedback Model

This model is a mechanism that combines variables from the pedagogy model, the domain knowledge model, and the learner model. The mechanism must take into account empirical evidence. For example, the data collected through the learning analytics are used to customize the content of the feedback, which was a standardized version of a possible solution to a combinatorial logic problem designed by an expert, i.e., the professor. In fact, there may be several possible solutions. For example, several Boolean equations, but it exists only one canonic equation.

Therefore, SCORM governed online learning content and learning management communication methods.

By adapting the SCORM package to the needs of the instructor, the SCORM resources can be used by the learner through the Connect I/O software downloaded from the learning management system (LMS). Learners test their solutions based on the SCORM application and get feedback on corrections and errors in their proposals. This SCORM application calculated the solution for the learner's truth table and the standard solution truth table from the professor. The standardized version of the solution to the specific problem has been presented in the dataset table.

Several types of metrics and standardized feedback were adapted to the different scenarios of the customized application being designed.

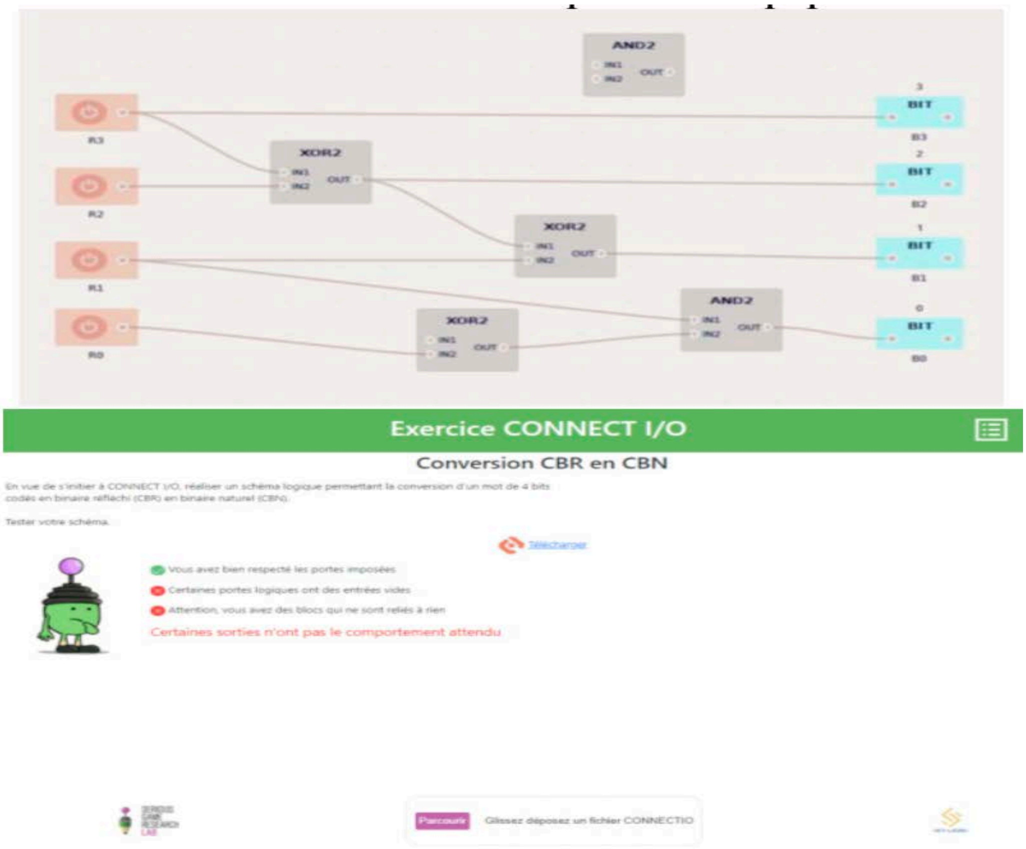


Figure 7. Package SCORM application

This SCORM application enabled learners to do practical work during the class and for homework. Learners have the opportunity to blend both synchronous and asynchronous learning in traditional flipped classroom. In fact, these interactive adaptation processes lead teachers to further design segmented learning resources and pathways. For example, breaking down the knowledge points into smaller modularized learning facilitates precision adaptation.

A well-developed learner model incorporates demographic characteristics, cognitive traits, types of motivation, cognitive strategies for the learning process, participation, self-regulation, personal traits, learning interests, prior knowledge, learning behaviors, preferences, etc. Existing models take into account the limitations of the small-scale adaptation methods needed to paint a changing picture of learner knowledge. Personalized prompts are given based on the learner's dynamics of failure and success during practice.

These may include inputs used, outputs used, logical gates not connected, bad behavior of outputs, number of tries, time spent in each practice, number of logical gates used, gates used. The advantages are automated data collection in each learning chapter, easy customization by the educator, easy integration of learner variables into the LMS Moodle, and facilitation of the development of skills in multiple exercises and applications.

CHAPTER 6. LEARNING ANALYTICS AND EVALUATION APPROACH

6.1 PRESENTATION OF MODULE

Training module D has been developed to be offered to computer science degree students, for the combinatorial and sequential logic teaching unit. It is accessible online on the <ET-LIOS> Connect IO platform.

The module of practical work, consisting of 3 separate exercises. The teacher writes each of these exercises. The latter offers them to the students during a session organized face-to-face at the university. The exercises can be completed during the hours set aside for the practical session, but they remain accessible afterward so that students can continue practicing. Each time a student submits an answer to one of the exercises, the tool tells them whether the solution is correct. If they make a mistake, it tells them which points are problematic.

6.1.1 Purposes of Data Processing

The platform hosting module D was equipped with an application developed by the INU. This application was used to collect and summarize data relating to its use in the course of the practical work. Each time a student submitted a solution to one of the exercises, a data record was created.

Our job was to process all the data collected in order to represent it in the form of graphs. These representations should help the INU to answer several questions:

- Do students benefit from being able to access the exercises outside class time?
- Does the 'learning companion' offer them effective help to progress?
- Can data analysis automatically identify students who are having difficulty (this will alert the teacher so that he/she can offer more specific support)?
- Can the data analysis help teachers to prepare their training modules?

The characteristics of the data files, the graphical representations, the algorithms used to process the data were presented.

6.1.2 Presentation of The Datasets

The initial dataset contained 685 records. Each record consisted of 14 data items.

The tables are presented in the annexes.

- 3 datasets were used to construct the graphical representations.
- 1 dataset was used to distinguish between the 3 exercises and to isolate the related data in 3 separate files.
- 10 data items were unusable or were not included in this processing.

A description of each item of data is available to determine, for each student,

The number of trials

Number of successful attempts

The number of attempts before success

Positive and negative feedback

Once we had isolated the data for each student, we extracted the information that will be used to construct the graphs: the number of trials, the number of successful trials, and the number of trials before success.

Finally, in order to be able to represent the students' actions over time (i.e., using chronological data), we extracted 5 pieces of information from the original file: the dates and times of the recordings, the positive and negative points, and the quality score.

6.1.3 Data Representation

The data for each exercise was processed in 3 distinct stages:

- A data exploration phase (histogram, whisker box, scatter plot)

- A data representation phase aimed at classifying pupils according to their performance

- A chronological data representation phase, to identify learning dynamics.

6.2 Data analysis

6.2.1 Introduction & Hypothesis

The research project concerns the construction of an adaptive learning environment. This involves the work of data collection and analysis based on the student profile, including descriptive analysis, diagnostic analysis, inferential analysis, predictive analysis, prescriptive analysis and cognitive analysis. The results of learning data analysis should facilitate the adaptive design of instruction, improve its quality, and enhance its impacts.

In this study, we conducted an experiment that allowed us to collect student data and then analyze it and draw some useful conclusions. We asked a homogeneous group of learners to solve three exercises related to course: logic combinatorial numbering and coding.

During this experiment, we measured, mainly, the following indicators: number of attempts, number of successes, number of unsuccessful attempts before success. This document provides a preliminary interpretation of learning experiments data. The experiment consists of measuring the engagement and performance of a group of students, with various indicators, in face of three different exercises with diverse characteristics. The number of participants for each exercise is given as follows: Exercise 1: 50 participants, Exercise 2: 50 participants, Exercise 3: 48 participants – two students did not participate.

Throughout this document, we shall assume that cognitive capabilities, learning interests, and the experiment conditions are similar across all the students involved so that the I.I.D hypothesis holds for the random variables considered in the analysis of data. Some preliminary conclusions about the learners' performance are included in each part of analysis. The value, efficacy and trustworthy of evaluation, and the limits of these results and assumptions would be discussed afterward. With the respect of this context, this experiment aims to explore the effective learning and identify didactic and instructional design principles. Three main metaphors including reinforce stimuli and response, knowledge acquisition and knowledge construction are applied to describe respectively how learning occurs lead to the changes of behavior and knowledge. Moreover, what the effective didactic and instructional design principles could adapt to heterogeneous situation in classroom setting. Furthermore, the objectives of tracking and analyzing students' learning process, learning outcomes are not only for identifying the efficiency, efficacy of learning process, the engagement and motivation of students. Indeed, learning needs, abilities and cognitive (knowledge) changes are simultaneously important as these are the criteria on the design of adaptive teaching and learning. There are some reflection points. First, what are the symbolism and interplay of the numbers of total trials, the number of successful attempts, the number of failure trails before success and the number of attempts after success? What are the symbolism and interplay of individual learning curve and memory curve? Are these variables could reflect the effective learning, significant learning and deep learning? On the other hand, how learning difficulties and risks could be diagnosed and then provide the guidance on the nature of predictive analytic and prescriptive analytic. Second, what are the factors can promote basic, generative and deep cognitive processing? How learning analytics benefit the design of didactics, instructional strategies, tutoring intervention and learning accompaniments. The purpose of interpretation of empirical results is to propose an adaptive learning analytic framework that can serve as the basis to adaptive learning design by means of examining, critically analyzing and summarizing the parameters of learning analytics and teaching adaptation that worth evaluation. Moreover, reflection of modelling values and contributions for adaptive learning mechanisms. The reference model of this adaptive learning analytic is originally proposed by Brusilovsky,(1998) and developed by Knutov et al., (2009). Learning analytics are based on the reflection of six dimensions: (1) what we can adapt, which involves the learning subject, topic, content, underlying learning objects, target or areas of adaptation and relationships between them. (2) What can we adapt to, which involves the adaptation parameters or criteria (i.e., cognitive abilities, knowledge mastery levels, learning performance, learning difficulties and so on. (3) Why do we need adaptation, which pertains to the learning goals and teaching objectives. (4) Where can we implement the adaptation, which pertains to application areas. (5) When can we apply adaptation, which involves the monitoring techniques, and underlying context and situation including cognitive processing, time aspects and constrains imposed by the environment. (6) How do we adapt? This involves the adaptation methods and techniques (i.e., adaptive tutorials organization, content presentation, adaptive hints, feedback, demonstrations, remedies, metacognitive scaffolding, support, suggestions and so on. With the respect of this, this data analysis focus on the exploration of learning performance, mastery levels of exercises (knowledge), motivation, learning effects and learning quality on certain analysis parameters. First, criteria derived from the analysis of data in box plots and bar charts were used to describe engagement based on the number of attempts in exercises, which initially determine the level of learners' learning efforts in each exercise and overall performance of three exercise. Secondly, the criterion for determining learning success is based on the number of successful attempts, which initially determines the learner's learning performance for each exercise, as well as the overall success of the three exercises. Third, the criterion for examining motivation and efficacy is based on the number of failed attempts before the first success. Fourth, the criterion used to classify learners' levels in each exercise is based on the above three analysis results, based on the median, average attempt, average success, and average failure before the first success in each exercise. In parallel, the proportion of learners performing below the third quartile is considered as a group with learning difficulties. Fifth, criterion that used to review learners' learning timeline are based on the analysis of chronological representation of data. This analysis can clearly show whether the learner completed the exercises in classroom or outside the classroom on the day of the practical work, whether the exercise was performed on other days, and whether the learner's success in the exercises depends on the assistance of professor or learning companion or simply through independent discovery learning. These can reflect learners' time management, learning methods, strategies, and preferences. Sixth, the standard is used to describe the learning curve, and the memory curve that are based on asynchronous learner's personal learning path chart. From the analysis of these data, it can reflect learners' learning motivation, learning beliefs, knowledge mastery probability etc.

The goal of learning data tracking and analysis is to understand students' learning processes, probability in mastery of knowledge, learning difficulties and to reflect on the adaptive learning design needs, appropriate tutoring and pedagogical tools, to improve the quality and impact of learning. This entails collecting and analyzing through their performance in the exercises, the level of engagement, the quality of learning success, as well as understanding their motivation by analyzing learning paths. Subsequently, learners' knowledge acquisition was analyzed based on their learning results in different exercises, learning behaviors, strategies, and learning outcomes, and students' learning levels were categorized to identify groups of students with excellent, moderate, difficult, and uncertain motivation.

Adaptive learning design is based on examination and reflection on the features and approaches of adaptivity and adaptability, the logic of content and knowledge organization, and the impact and effects of cognitive processing methods and strategies. Therefore, we evaluate learning significance through learning analytics based on these indicators.

With personalized analytics, individual learning progress can be observed, and adaptive learning content, assessment, sequences and activities can be recommended.

A multidimensional evaluation framework for identifying meaningful and deep learning would be provided based on learning data analysis so as to guide the future design of adaptive instruction and learning. This study addresses the current research gaps and deficiencies of the application of learning science in data-driven adaptive learning analytics and provides guidance for future adaptive learning design engineering. This study enables learning target audiences, including instructional engineers, data scientists, researchers in the fields of educational psychology, cognitive science, and artificial intelligence, to gain new insights into instructional analytics, innovative methods, and technological tools.

6.2.2 Analysis of Engagement

This section is devoted to the analysis of the number of trials, done by students, for each of the three exercises considered in this experiment. For that, we consider the distribution of students across the number of trials. The subsections are devoted to the conclusion of each considered exercises. The number of attempts can reflect on learner's involvement, initiation and persistence. In parallel, the increase in the number of attempts can reflect learner's attitude and decisions towards the exercises. More attempts may represent a deeper engagement for the learner with the materials. Learners may be driven by different reasons based on their interests, beliefs, learning goals or as a personal challenge. The analysis of learning engagement can reflect the applicability, difficulty, and learner adaptability of different exercise contents. However, it is difficult to infer from the total number of attempts that learners have difficulty with knowledge points in specific exercises. The total number of attempts does not represent learner's level, memory curve, cognitive processing method, knowledge construction or schema assimilation. The goal of adaptive learning is to diagnose learning needs and help students who are in learning difficulties, to transform ineffective and repetitive learning into creative learning and deep cognitive generation modes. As such, adaptive learning is well suited to facilitate learners' motivation and engagement. In addition, for learners who have already mastered the exercises, cognitive tools, those designed to reinforce learning, facilitate the reconsolidation and integration of knowledge and improve complex problem-solving abilities and learning flexibility.

a) Results for exercise 1

The number of trials is described by the following figures:

Histograms: histograms group the values taken by a continuous quantitative variable into ranges. The height of each < bar > in the graph depends on the numbers of data in the corresponding interval. In simple terms, histograms help determine the distribution of data and the presence of abnormal values.

Moustache Boxes: The exploration of the data ends with its statistical representation in the form of a whisker box.

Each graph can be read as follows:

- Lower edge of the box: 1st quartile (Q1), also known as the lower quartile, is equal to the 25th percentile of all values in the sample, ranked from smallest to largest.
- Line in the box: 2nd quartile (Q2), also known as the value of the median, is equal to the number of all values in the sample from the smallest to the largest 50%.
- Upper edge of the box: value of the 3rd quartile (Q3), also known as the upper quartile, is equal to the 75th percentile of all the values in the sample from the smallest to the largest.
- The difference between Q3 and Q1 is also known as the Inter Quartile Range (IQR).
- End of box and cross (if present): extreme value.

For exercise 1, the histogram below represents the number of students according to the number of trials performed.

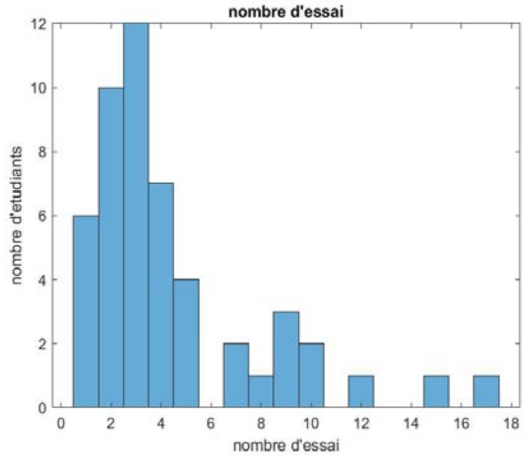


Figure 8. Histogram of the number of trails for exercise 1

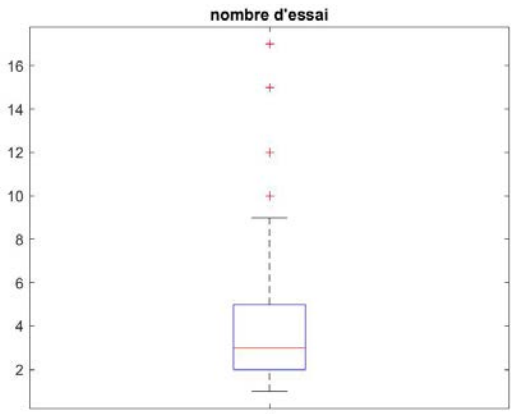


Figure 9. Box plot of the number of trails for exercise 1

The observations for Exercise2 based on Figure 8 and Figure 9:

With regard to the distribution of learning engagement characteristics amongst participants, there were more learners (78%) trying between 1-5 times than less learners (22%) trying between 7-17 times. The majority of the learners had tried 2-4 times (58%), and very few learners had tried more than 10 times (6%). The mean number of trials was 4.46, which was closer to the standard deviation (SD=4.48). The maximum of trials was 17 times and the minimum of trials was 1 attemp

(Range=16). The majority (higest ordiante) had total trials for 3 times, which was same as the median(median=3), and interquatile range (IQR=3). The lower quatile (Q1= 2), and the upper quatile (Q3= 5), which could be used as the criteria for recognizing the distribution trend and differentiating different levels of learning engagement. Based on these data, we observed that 66% of learners (33 out of 50) tried the exercise between 2-5 times were recognized as the group in overall level of trying the exercise. There were 12% (6 out of 50) of learners tried only 1 time, and 22% (11 out of 50) of learners tried more than 4 times, which were considered as out of scope of general level of trying, there were some extreme value or outliers. Figure 1 presented the distribution of students trials and degree of volatity for exercise by histogram. Figure 2 presented the average shape of the box plot and whisker for signs of symmetry or skewing as well median, lower and upper quartile, inter quartile range (IQR), and outliers.

b) Results for exercise 2

The number of trials is described by the following figures:

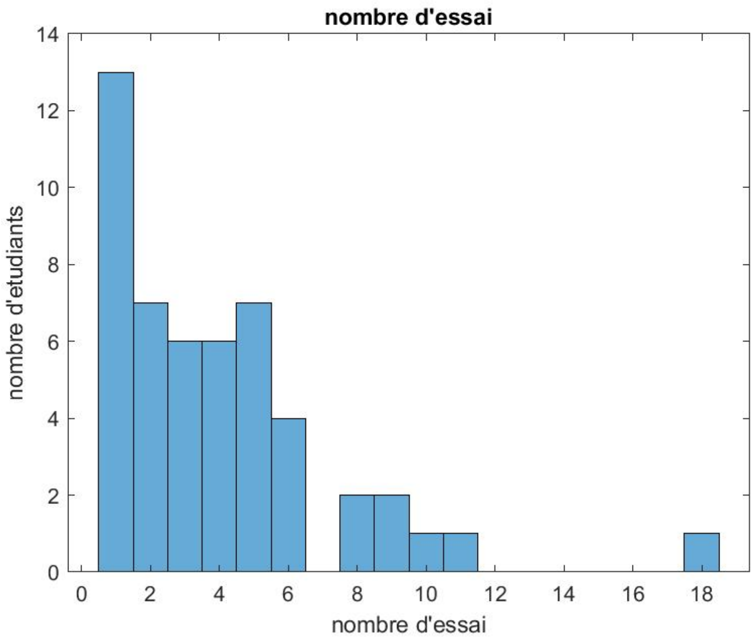


Figure 10. Histogram of the number of trails for exercise 2

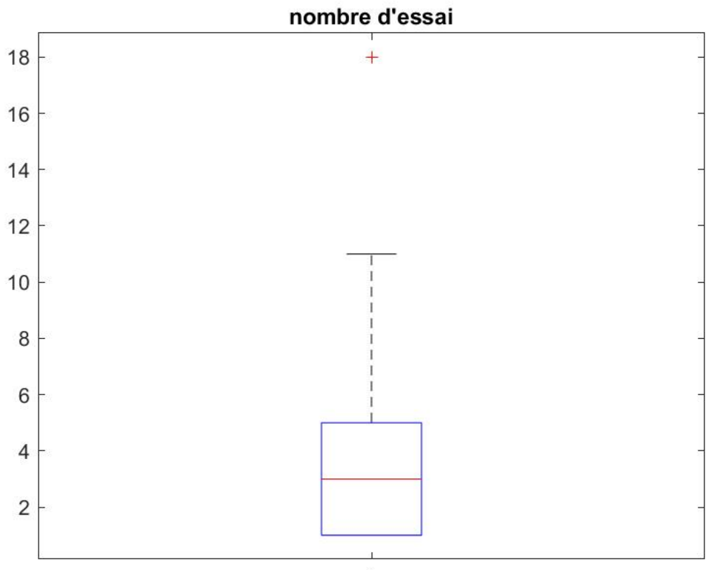


Figure 11. Box plot of the number of trials for exercise 2

The observations for Exercise 2 based on Figure 10 and Figure 11:

With regard to the distribution of learning engagement characteristics amongst participants, there were more learners (78%) trying between 1-5 times than less learners (14%) trying 8-18 times. The majority of the learners had tried 1-3 times (52%), and very few learners had tried more than 10 times (6%). The mean number of trials was 4.02, which was bigger than the standard deviation (SD=3.4). The maximum of trials was 18 times and the mimum of trials was 1 time (Range=17). 26% learners (13 out of 50) attempted 1 time (highest ordinate), which was the same as the lower quartile(Q1=1). The upper quartile was 5(Q3=5). The interquartile range (IQR=4) was the nearly same as its average number. This could be used as the criteria for recognizing the distribution trend and differentiating different levels of learning engagement. 22% of learners have tried the exercise more than 5 times, which were considered as out of scope of general level of trying, there were some extreme value or outliers. Although its range was larger to the exercise 1, this may mean that learners have heterogeneous levels of engagement and motivation to practice the exercises. The participants had less motivation to try more times in exercise 2. Students who tried more than 5 times could be outside of the average level of engagement. Students who tried less times could indicate that they might have achieved the success and understood the task.

c) Results for exercise 3

The number of trials was described by the following figures:

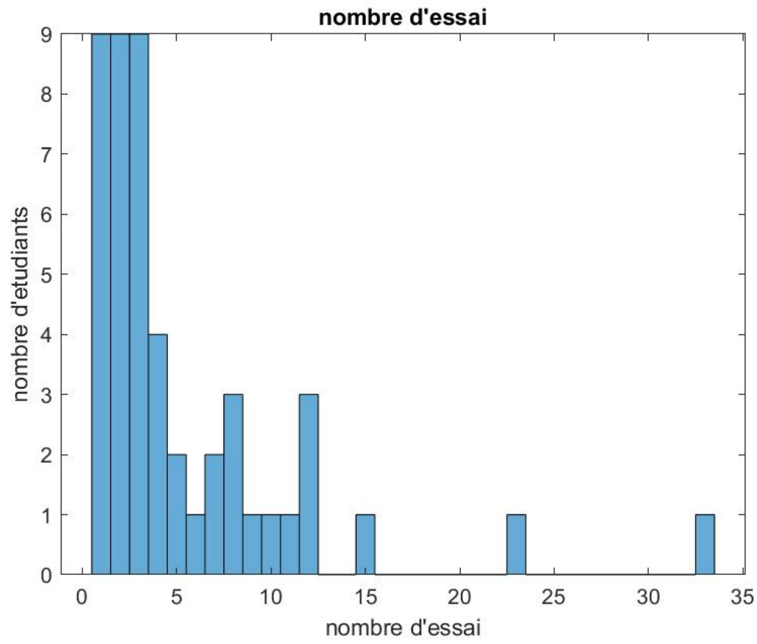


Figure 12. Histogram of the number of trials for exercise 3

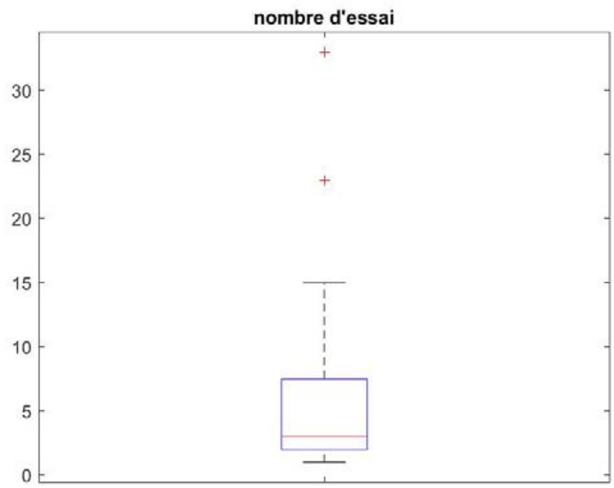


Figure 13. Box plot of the number of trials for exercise 3

The observations for Exercise3 based on Figure 12 and Figure 13:

With regard to the distribution of learning engagement characteristics amongst participants, there were more learners (75%) have practiced between 1 and 7 times than less learners (16.7%) trying between 10-34 times. The majority of learners had tried 1-3 times (56%), and very few learners had tried more than 15 times (6%). The highest ordinate of leaners' trials contains 1, 2, and 3 times that represented respectively 9 learners in each bar. The mean number of trials was 5.43, which was smaller than the standard deviation (SD=6.24). The lower quartile was 1(Q1=1), and the upper quartile was 7(Q3=7). The interquartile range was 6 (IQR=6). There were 25% (12 out of 48) of learners tried more than 7 times, which could be considered into the groups that out of scope of general level of trying, there were some extreme value or outliers.

The maximum of trials was 33 times and the minimum of trials was 1 time(Range=32). The range was larger to the exercise 1 and exercise 2, this may mean that learners have very heterogeneous levels of skills, engagement and motivation to practice the exercise 3, some of them may encounter the difficulty before, during or after the practices. There were 2 students did not participate in exercise 3.

6.2.3 Analysis of Learner Success

This section is devoted to the analysis of the number of students' successes in each of the three exercises considered in this experiment. For that, we consider the distribution of students across the number of successes. The subsections are devoted to the conclusion of each considered exercise. The number of successes can reflect the learner's learning outcomes for different exercises. Learners may understand and master procedural knowledge. The success rate of learners helps teachers and learners reflect on the latter's capacity to master knowledge. Therefore, teachers and learners are able to promote significant deep cognitive processing strategies based on the evidences in these exercises. Teachers, or the automated system, may recommend the subsequent learning levels, learning paths, practice content and activities based on the evaluation of the numbers of successful attempts. They may also organize the appropriate tests and Q&A to verify the authenticity and credibility of the learning successes. In addition to the tutoring support, such adaptive learning scenarios should also include self-regulation, self-reflection, self-efficacy, adaptive cooperative learning and peer assessment.

a) Results for exercise1

The number of successful trials across students is described by the following figures:

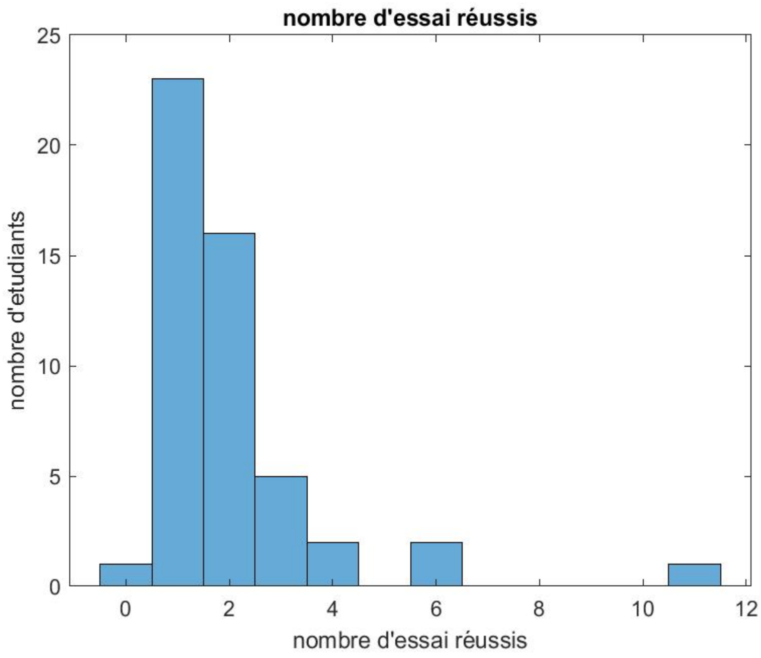


Figure 14. Histogram of the number of successes for exercise 1

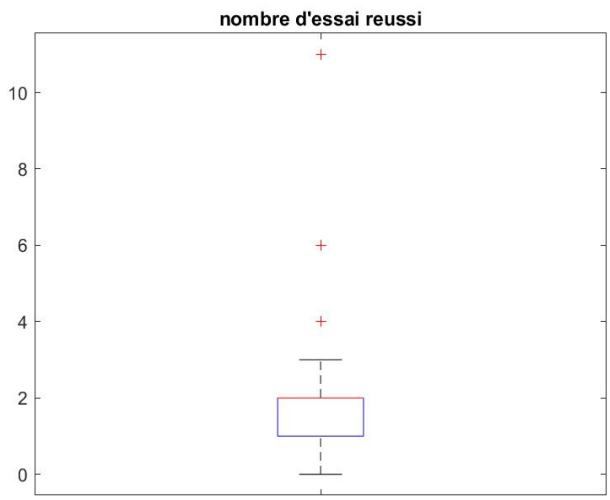


Figure 15. Box plot of the number of successes for exercise 1

The observations for Exercise1 based on Figure 14 and Figure 15:

With regard to the learning success characteristics amongst participants, there were more learners (78%) who have been successful on exercise 1 between 1-2 times than less learners (10%) who have been successful at least 4 times. The mean number of successes was 2.02 times, which was smaller than standard deviation (SD= 1.6).

The highest ordinate (23 out of 50), 46% of learners have been successful for 1 time, which was the same as the lower quartile (Q1=1) and its interquartile range (IQR=1). The upper quartile (Q3=2), which was the same with the median (median=2). The maximum number of the success was 11 times, the minimum success was 1 (range=10). Most of the learners have tried the numbers of success only no more than 2 times. There were 20% (10 out of 50) of learners have tried the success for more than 2 times, which could be considered as the group out of scope of general level of trying the sucess, there could be some extreme value or outliers. There was a learner did not try the success in exercise 1. The failure rate was 2%.

b) Results for exercise 2

The number of successful trials across students is described by the following figures:

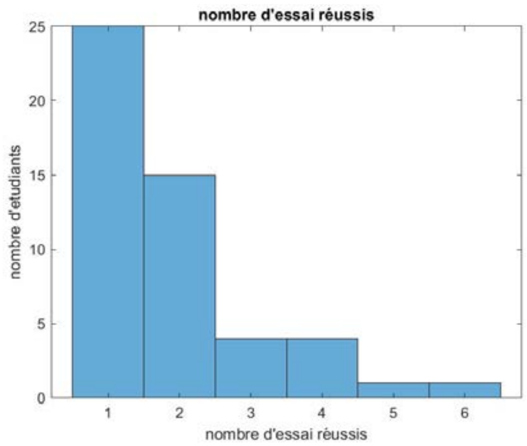


Figure 16. Histogram of the number of successes for exercise 2

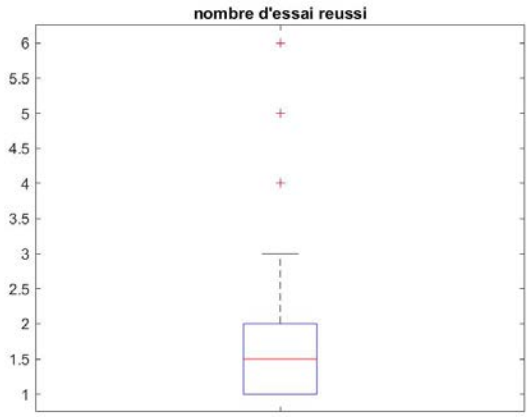


Figure 17. Box plot of the number of successes for exercise 2

The observations for Exercise2 based on Figure 16 and Figure 17:

With regard to the learning success characteristics amongst participants, there were more learners (80%, 40 out of 50) who have been successful on exercise 2 between 1-2 times than fewer learners (24%, 12 out of 50) who have been successful at least 3 times. The mean number of successes was 1.88 times, which was bigger than the standard deviation (SD= 1.22). The highest ordinate (25 out of 50), 50% participants have been successful for 1 time, which was the same as the lower quartile (Q1=1) and its interquartile range (IQR=1). The upper quartile (Q3= 2), the median=1.5. Most of the learners have tried the numbers of success only less than 2 times.

There were 24% (12 out of 12) tried the success more than 2 times, which may be considered as the group out of scope of general level of trying the success, there could be some extreme value or outliers. The maximum number of trying the success was 6 times, and the minimum number of trying the success was 1(Range=5). Every learner has tried the success and in less than 7 times in exercise 2. This indicated that the motivation of trying the success might be not obvious as learners may have no encountered learning challenges or difficulty in exercise 2.

c) Results for exercise 3

The number of successful trials across students is described by the following figures:

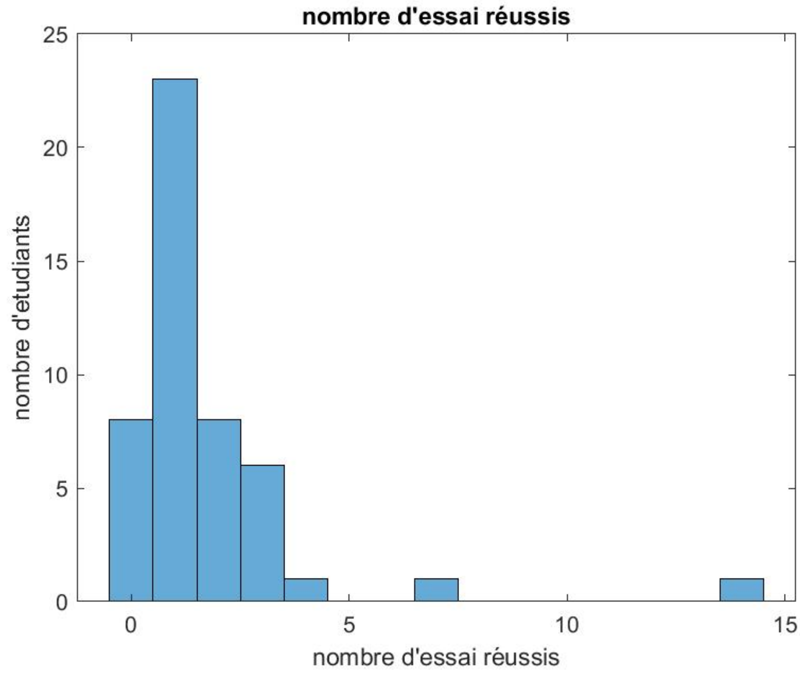


Figure 18. Histogram of the number of successes for exercise 3

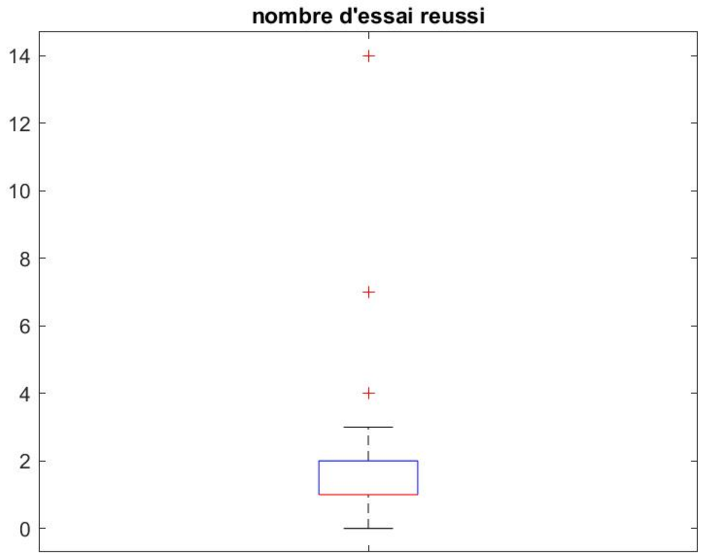


Figure 19. Box plot of the number of successes for exercise 3

The observations for Exercise2 based on Figure 18 and Figure 19:

With regard to the learning success characteristics amongst participants, there were more learners (77%, 37 out of 48) have been trying the success on exercise 3 between 1-3 times. 48 % of learners

(23 out of 48) have only tried the success for 1 time, which was the highest ordinate that represented in the histogram.

The mean number of trying the success was 1.7 times, which was smaller than standard deviation (SD= 2.19). The medium number was 1(median=1), which was the same as the lower quartile (Q1=1) and its interquartile range (IQR=1). The upper quartile (Q3= 2). There were 18.75% (9 out 48) students who tried the success for more than 2 times, which could be considered as the group out of scope of general level of trying the sucess, there could be some extreme value or outliers. The maximum number of trying the success was 14 times. The minimum number of trying the success was 0 time (range= 14). The percentage of being able to be successful for at least 4 times was 6.25%. Learners who have not been successful recording took account for around 16.7% (8 out of 48). This indicated that there were some learners might have difficulty in trying the success as they may lack of understanding of conceptual knowledge, critically logical thinking, problem thinking or time management and so on.

In exercise 3, the standard deviation was greater than the average number of student success, which means that the data was less reliable and stable. The median and lower quartiles overlap on a horizontal line, this data set was considered deviant from the norm. Among the 40 participants, excluded 10 learners who never succeeded or participated, the average number of participants' success was 1 time.

6.2.4 Analysis of Learner’s Path Towards Success

This section is devoted to the analysis of the number failures before the first successful try, attempted by students, for each of the three exercises considered in this experiment. For that, we consider the distribution of students across the number of failures before their first success (i.e., how many students have had N failure before their first success, for each value of N).

Analyzing the number of unsuccessful attempts before students' success can reflect their efforts, the speed or efficacy of knowledge acquisition, and the learning curve. At the same time, these data processes can be gathered and analyzed to help us understand students' learning paths, attempts, and behaviors before they reach their learning goals. This can help educational practitioners to analyze learning strategies, rationalize the learning design, and help them to reflect on adaptive learning paths, efficiency, and quality with learning tools and learning accompaniment.

a) ***Results for exercise1***

The number of attempts before success is described by the following figures:

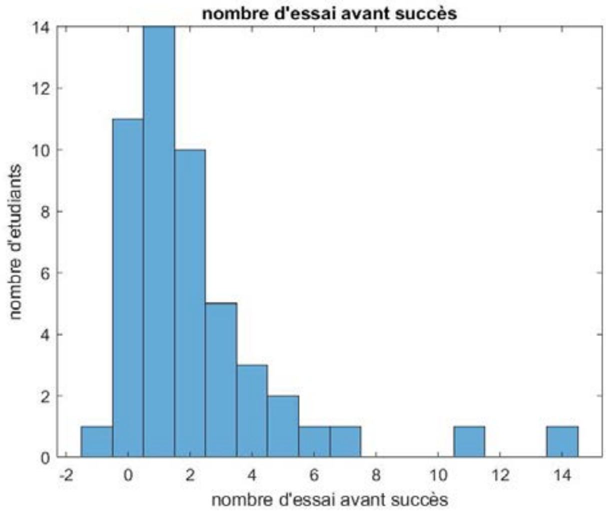


Figure 20. Histogram of the number of attempts before success for exercise 1

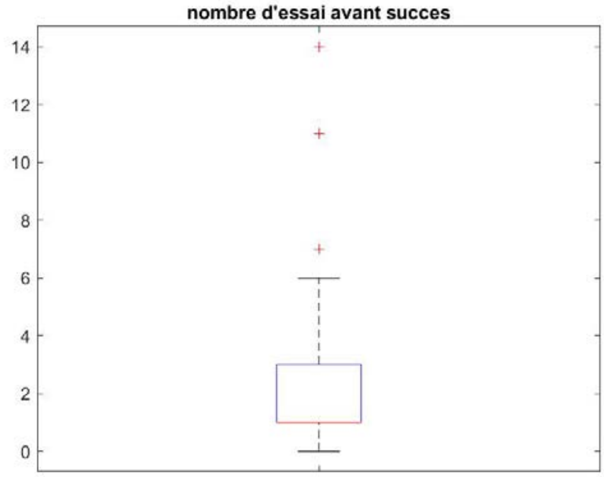


Figure 21. Box plot of the number of attempts before exercise 1

The observations for Exercise1 based on Figure 20 and Figure 21:

With regard to the number of trying failure before the first success characteristics amongst participants, there were more than half of learners, nearly 59.18% (29 out of 49) who have been trying the failure before success on exercise 1 for 1-3 times.

The mean number of successes was 2.52 times, which was similar to the standard deviation (SD= 2.53). The highest ordinate (14 out of 49), 28.57% of learners have been trying the errors for 1 time to achieve the success, which was the same as the medium level (median=1), and the lower quartile (Q1=1). The upper quartile (Q3= 3), and its interquartile range was 2 (IQR=2). There were 18.37 % (9 out 49) learners have tried at least 4 times of errors before success, which could be considered into the group that out of scope of general level of trying the errors before the sucess, there could be some extreme value or outliers. The maximum number of trying the errors before success was 14 times (Range=14). There were 22.45% (11 out of 49) learners have no trying any errors, in other word, they have been able to try the success immediately in the first time. There was a learner who have no record of doing the practical work.

b) Results for exercise 2

The number of attempts before success is described by the following figures:

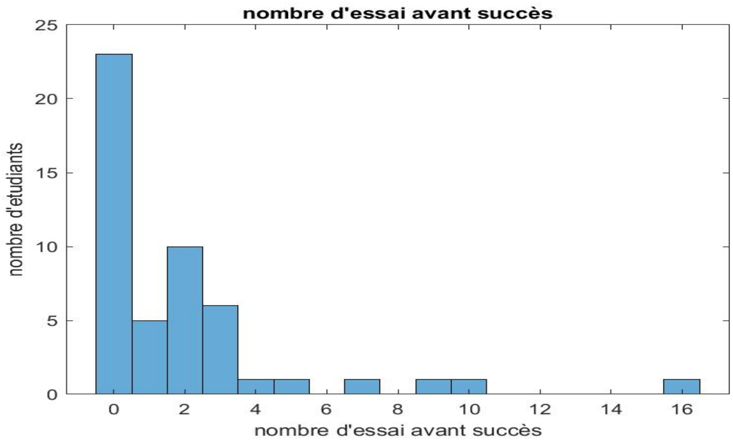


Figure 22. Histogram of the number of attempts before success for exercise 2

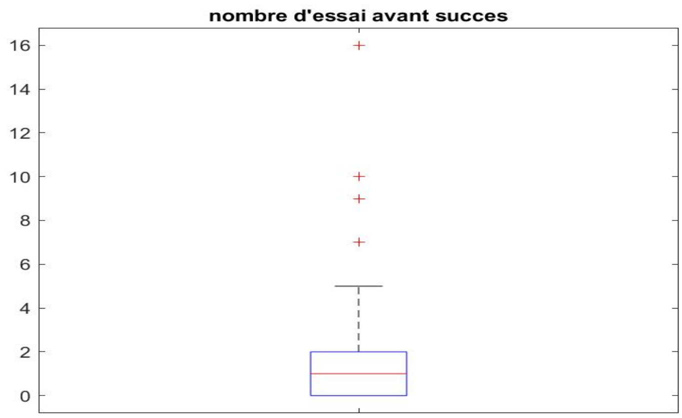


Figure 23. Box plot of the number of attempts before success for exercise 2

The observations for Exercise2 based on Figure 22 and Figure 23:

With regard to the number of trying failure before the first success characteristics amongst participants, there were more (42%, 21out of 49) learners who have been trying the failure on exercise 2 for 1-3 times to achieve the first success. There were less (12%, 6 out of 50) learners who have been trying the errors at least 4 times before the first success.

The mean number of trying the errors before the first success was 1.88 times, which was smaller than the standard deviation (SD= 2.72). The majority (highest ordinate) of learners (46%, 23 out of 50), who have been trying the practices and achieved the success immediately in first time. The medium=1, and the lower quartile (Q1=0). The upper quartile (Q3) was 2, and its interquartile range was 2 (IQR=2). There were 24 % (12 out of 50) learners have tried the errors for at least 3 times, which may be considered into the group that out of scope of general level of trying the errors before the sucess, there could be some extreme value or outliers. The maximum number of trying the errors before the first success was 16, and the minimum number of trying the errors was 0 (Range=16). Every learner had successful record of trying the practical work in exercise 2.

c) Results for exercise 3

The number of attempts before success is described by the following figures:

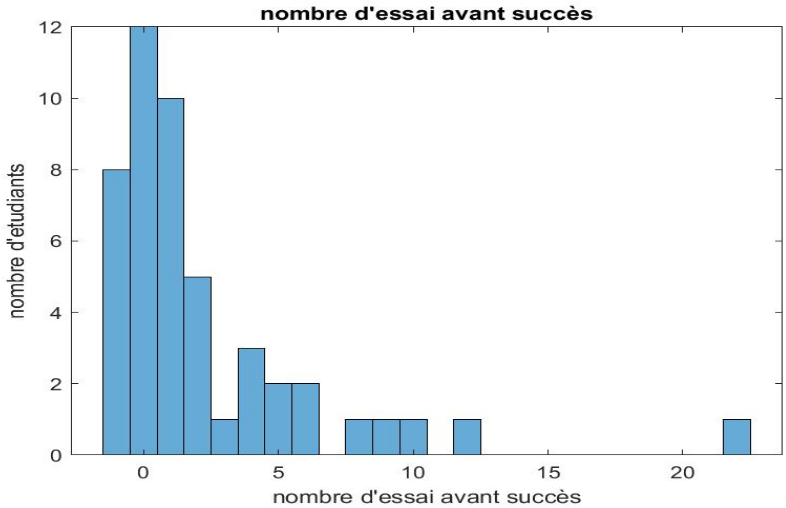


Figure 24. Histogram of the number of attempts before success for exercise 3

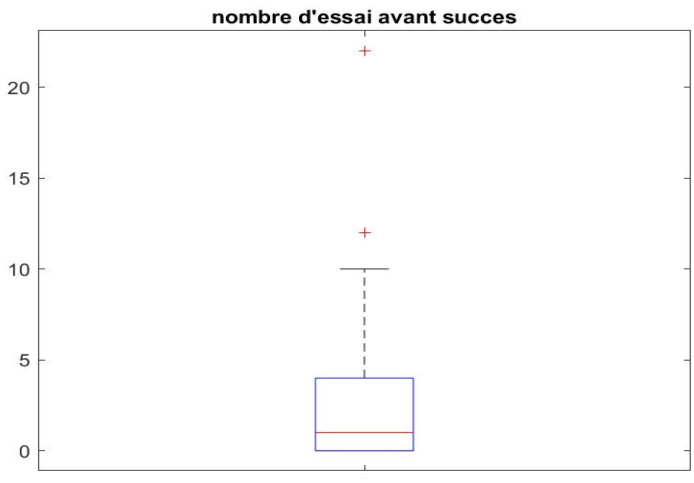


Figure 25. Box plot of the number of attempts before success for exercise 3

The observations for Exercise 3 based on Figure 24 and Figure 25:

With regard to the number of trying failure before the first success characteristics amongst participants, there were more half of leaners (56.25%, 27 out of 48) who have been trying the errors for less than 2 times to achieve the first success. There were 25% of students (12 out of 48) have been trying the practices and achieved the success immediately in first time, which represented the highest ordinate of bar chart. There were less students (27.08%, 13 out of 48) have to try the errors at least 3 times before the first success. The average number of trying the errors before the first success was 2.92 times (mean=2.92), which was smaller than the standard deviation (SD= 3.87). The medium level was 1(median=1), and the lower quartile (Q1=0). The upper quartile (Q3=4) was the same as its interquartile range was 4 (IQR=4). The maximum number of trying the errors before the first success was 23 times, the minimum number of trying the errors before the first success was 0 time (range= 23). There were 18.75 % (9 out of 48) leaners have been trying the failure at least 5 times to achieve their first success, among these participants, there were two of them have been trying the errors more than 10 times, respectively for 11 and 23 times. There were 16.7% (8 out 48) learners have no successful record of trying the practical work in exercise 3. These learners could be considered into the group that out of scope of general level of trying the errors before the sucess, there could be some extreme value or outliers.

In this exercise, the standard deviation was higher than the mean, the median was skewed toward the lower quartile, the data were unstable and scattered. Nearly half, 46% (22 out of 48) of learners succeeded by failing at most once. Groups where learners tried the errors at least 4 times before first success, it was therefore considered to be in the situation of learning difficulty. These student numbers include those in the upper quartile and above, which took account of 75% and above of the total population.

6.2.5 Preliminary Conclusion of Learner’s Performance

For the three exercises, it is important to know the average number of attempts, chances of success, levels of difficulty, rate of failure to reveal learners’ engagement, motivation, effort for success and their learning gains. Therefore, we were able to observe the completion of the exercise from the average number of attempts and successes of learners, the difficulty of the exercise through the number of failures, and learners' engagement and effort to observe their learning enthusiasm and motivation. Therefore, for these indicators, our standard formulation was based on the evidence from impact measurement and human judgment to describe the effectiveness of learning and possibility of knowledge change. The measurement based on the number of attempts, successes, and failures before success in each exercise can be determined as the indicators to evaluate the learning performance and impact.

The criteria of the analysis are based on the observation of the data from the histogram and the box plot. For each exercise, we measured learner' learning level by lower quartile, upper quartile, median, etc., combined with the distribution of learners' performance in each exercise, through the data of the histogram to calculate the mean, standard deviation, range, etc. to strengthen the reliability of data analysis, authenticity and logic. How the degree of data dispersion affects the quality of learning analysis, how the inaccuracy and instability of data analysis could be evaluated, and improve the authenticity and reliability to provide effective evidence for supporting the construction of adaptive learning was the objective of the research.

The first representation related to the exploration of the data show different levels of success according to the exercises. Exercise 2 appears to be the least difficult, with 23 out of 50 learners passing it on the first try. Exercise 3 appears to be the most difficult, with a higher number of attempts and 8 students never having succeeded ("*user_002, user_010, user_021, user_022, user_027, user_030, user_042, user_045*"). Thus, in order to determine learners 's performance and level of knowledge, it is necessary to continue to distinguish between the 3 exercises.

The different percentage of learners practiced at least 10 attempts indicated that the related level of difficulty of each exercise. It was observed that the average number of attempts was the highest in exercise 3. The probability of a learner trying at least 10 times in exercise 3 was the highest. All learners have recorded the successful trial in Exercise 2, and the failure rates for Exercises 1 and 3 were 2% and 16.67%, respectively.

Based on the results of the previous sections, the following trends were described:

- Concerning learning engagement and motivation. Exercise 1 seem to be more attractive than Exercise 2. This was clearly emphasized in the average number of trials and the population’s distribution. Moreover, students seem to be more willing to try multiple times on Exercise 3 in comparison to the other exercises. The results showed that average number of attempts were respectively 4.46, 4.02, 5,43 times on exercise 1, 2,3. The probability of trying the exercise more than 10 times were 10%, 6% and 16.67%.

- Concerning the learning success. The preliminary observations revealed that the success rate of students in Exercises 1 and 2 was higher than in Exercise 3. There were more students who scored well quickly in Exercise 2 compared to Exercises 1 and 3. The differences between exercise 1 and exercise 2 was moderate, while the difference with exercise 3 was more flagrant as it can be emphasized in the average number of student success, probability of being successful at least two times and three times. The results showed that average number of student success were respectively 2.02, 1.88, 1.7 times on exercise 1, 2,3. The probability of being successful at least two times were 52%, 50%, 18% respectively. The probability of being successful at least three times were 20%, 24%, 19% respectively.
- Concerning the learning effort. This could be revealed from the errors and learning paths toward the success. The average number of required attempts before the success were 2.12, 1.88, 2.97 times respectively.
- Concerning the possibility of learning progress and gains. This could be reflected from the probability of success after the attempts between 0-2 times. The results showed the probabilities of success in less than 2 attempts were 70%, 76%, 56% respectively.
- Concerning the learning difficulty and risks. This could be revealed from the outliers and extreme values out of scope of interquartile range and rate of failure. The rates of failure were 2%, 0%, 16.67% respectively in three different exercises.
- Concerning the level of learning material's difficulty. Exercise 3 seems to require more effort (more failures) before the first success, meanwhile, Exercise 2 seems to be easier to obtain in overall and showed the best results.

Following analysis would be conducted for measuring learning performance and classification of levels. Learning performance are not only influenced by the intelligent tutoring, timely feedback but also effective cognitive strategies. One of the objectives of learning analytics are to group learners' profiles and design adaptive and personalized learning pathways.

The conclusion of this section depends on our assumptions on data, and specially the I.I.D hypothesis. If the learners' capabilities and skills are very different, the results should be corrected and/or similar analysis should be conducted on each category/cluster of learners.

Moreover, the conclusions could be refined by considering the order of the exercises during the learners' experiment, in order to correct any "learning effect" across the exercises.

6.2.6 Groupings by Learners Levels

An important question at the origin of the <ET-LIOS> project was to determine to what extent "online" practical work allowed the professors to identify what kind of learners' behavior indicated the learning performance and difficulty. To help answer this question, a reflection on the methods allowing the classification of learners' levels was carried out.

This section is for analyzing the learners who meet 2 or 3 of the following criteria simultaneously, including a maximum number of trials, a maximum number of successes, and a maximum number of trials before first success.

The value of this maximum was consistent with the difficulty of the exercise. This methodology allowed us to identify the proportion of learners who were in good performance, and who were in difficulty.

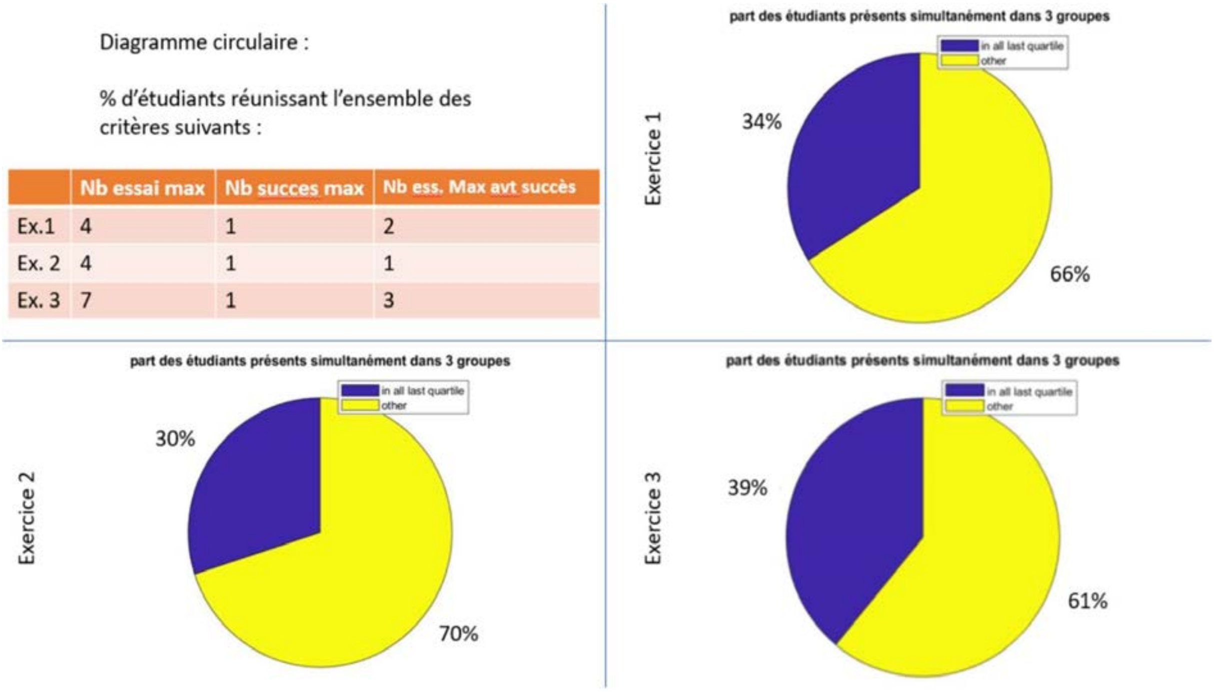


Figure 26. Circular diagram visualization of grouping learners' levels

Firstly, we wanted to represent the share of learners whose performances placed them strictly below the third quartile (75% of students) for 3 criteria simultaneously: the number of attempts, the number of successes and the number of trials before success. The values of the 3rd quartile being different from one exercise to another, considering its level of difficulty, this led us to 3 distinct representations.

For each exercise, the yellow group brings together learners who have demonstrated remarkable behavior on at least one of the three criteria. We wanted to explore this yellow group in more detail, trying to isolate the portion of students whose "remarkable" behavior stems from difficulty completing an exercise. We agreed that a learner in learning difficulties was at or above the 3rd quartile for 2 criteria simultaneously: the number of attempts, and the number of attempts before success.

Table 10. Criteria of measuring learner in learning difficulties

Exercises	Number of trials	Number of attempts before

	Minimum	success Minimum
Exercise 1	5	3
Exercise 2	5	2
Exercise 3	7	4

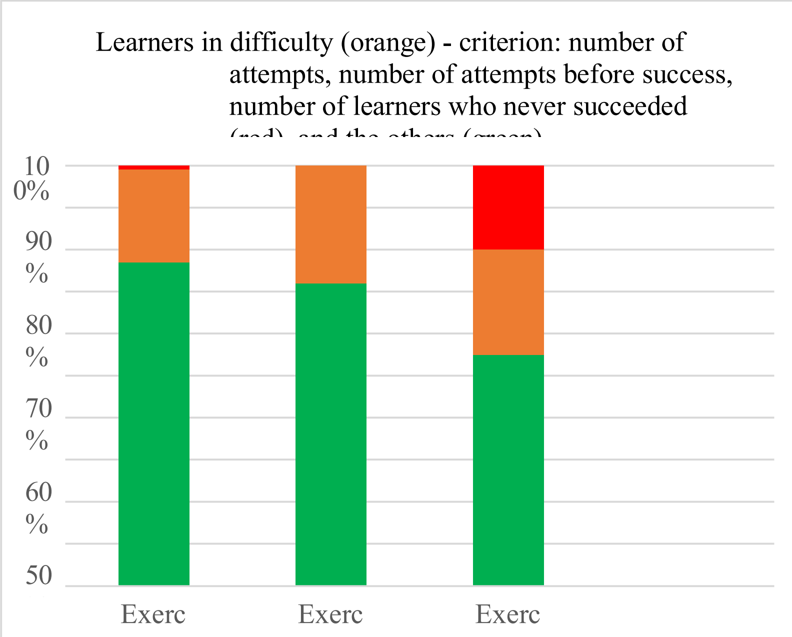


Figure 27. Learners in difficulty

From this figure, we wanted to precisely identify those learners are shown in orange, in addition to learners who have never passed (represented in red, list on page 15). It is necessary to determine whether learner faced difficulty in one exercise have also encountered other types of problems. Likewise, it is interesting to determine whether a portion of workforce is successful over all the exercises. We therefore agreed on criteria allowing us to form 3 different groups.

Table 11. The representation of learners' performance levels

Students who were in difficulty	Students in difficulty Students who never succeeded	

“Good performance” learners, having no problem completing the exercise	Learners whose number of attempts before success=0 (Students who tried the exercise without any failure)	
Average performance learners	Learners not found in one of the two previous groups	

This allows 4 groups to emerge, including learners who had faced difficulties on at least two exercises, learners who were struggling in one of exercises, learner who have never in difficulty and “good” at most 1 time, learners who were good on at least two exercises and never in difficulty. The number of learners in each group is represented in the following table.

Table 12. The number of learners in different levels of difficulty

Learners in difficulty on for at least 2/3 exercises	Learners who were struggling in an exercise (1/ 3 exercises)	Learners who are never in difficulty and “good” at most 1/ 3 exercises	“Good Performance” learners on at least two exercises and never in difficulty in 2/3 exercises
15	**14**	**14**	**7**

There are three important limitations to this classification:

- First of all, the orange group only takes into account students who have passed at least once, which excludes those who have never succeeded (8 people for exercise no. 3). The latter appear in red, and we considered it more acceptable to also count them as learners in difficulty.
- Next, the green striped group counts all the learners who passed on the first try. The exercises can be carried out in practical work in the presence of the teacher, it is not excluded that the latter can “help” his students. It is therefore appropriate to observe in what proportion leaners produce more than one attempt or the same exercise, and whether the following test, the one just after the first success in TP was also successful.

- Finally, the parameters allowing us to say that a learner was “good” or “in difficulty” were discussed. It appears interesting to compare several criteria, in order to determine the way in which this impacts the physiognomy of the groups (learners in difficulty on 2 or 3 exercises, learners in difficulty on a single exercise, learners never in difficulty and "good" on a maximum of one exercise, learners never in difficulty and “good” at least on two exercises).

Below is a table presenting total number of learners affected by each criterion mentioned during various work meetings.

Table 13. The number of learners’ attempts before success

	Number of Students		
Criteria	**Exercise 1**	**Exercise 2**	**Exercise 3**
Students who have never succeeded	1	0	8 (+2 never tried)
Number of attempts & number of attempts before success	11	14	10
Number of attempts before success	14 (+ 3*)	22 (+ 8*)	12 (+ 2*)
Learners who were successful in the first time of the exercise	11	23	12
Learners with at most one failure before their first success	25 (+ 14*)	28 (+ 5*)	22 (+ 10*)

* Additional learners, compared to the criterion of the previous line

By retaining criteria 3 and 5 in place of criteria 2 and 4, we obtain significantly different groups, the tables which represented these different learning groups can be found from the annexes:

Learners faced difficulties on minimum 2 exercises in two groups: the ancient group represented 15 learners, which were "*User_002, User_005, User_010, User_012, User_15, User_018, User_021, User_022, User_025, User_031, User_034, User_036, User_041, User_042, User_043)*

". The new group represented 21 learners, that presented 6 more persons, which were "*User_000, User_011, User_020, User_023, User_024, User_032".*

Learners struggling with an exercise: the ancient group represented 14, which were "*User_000, User_003, User_007, User_011, User_020, User_023, User_024, User_027, User_030, User_032, User_040, User_045, User_046, User_049*", the new group represented 12 learners, which were "*User_003, User_004, User_007, User_026, User_027, User_030, User_040, User_044, User_045, User_046, User_047, User_049*".

Learners who were never in difficulty and "good" at maximum of 1 time: the ancient group represented 14 learners, which are "*User_004, User_006, User_008, User_009, User_016, User_019, User_026, User_028, User_035, User_037, User_039, User_044, User_047, User_048*", the new group represents only 1 learner, which was User_019.

Learners whose performance were good on at least two exercises and never in difficulty: the ancient group represented 7 learners, which were "*User_001, User_013, User_014, User_017, User_029, User_033, User_038*", the new group represented 16 learners, with 9 more different learners, which were "*User_006, User_008, User_009, User_016, User_028, User_035, User_037, User_039, User_048*".

All the data used to form the new groups are available in the "*level_etudiant_e1-e2-e3_criteres09-2022.xlsx" file ("niveau_etudiant_e1-e2-e3_criteres09-2022.xlsx*".).

The number of learners in each group is represented in the following table.

Table 14. The change in number of learners in different levels of difficulty

Learners in difficulty on at least two exercises for at least 2/3 exercises	Learners who were struggling in an exercise for 1/3 exercises	Learners who are never in difficulty and "good" at most 1/3 exercises	"Good Performance" learners on at least two exercises and never in difficulty for 2/3 exercises
21 (+ 6*)	**12** (- 2*)	**1** (- 13*)	**16** (+ 9*)

* The change in number of learners comparing to former groups

Table 15. Learners' engagement via chronological representation

(white)	Les étudiants ont posté leurs réponses uniquement pendant les heures de TP
(yellow)	Les étudiants ont posté leurs réponses le jour du TP, mais à une heure ou il n'avait plus l'encadrement de leur professeur
(light blue)	Les étudiants ont postés leurs réponses le jour du TP, pendant et en dehors des heures d'enseignement
(orange)	Les étudiants ont postés toutes leurs réponses après le jour du TP
(red)	Les étudiants n'ont jamais posté de réponse

	groupe 1	groupe 2	groupe 3	groupe 4	groupe 5
Exercice 1	49	1	0	0	0
Exercice 2	29	9	10	2	0
Exercice 3	4	18	2	24	2

Nombre d'étudiant par groupe, pour chaque exercice

6.2.7 Chronological Representation

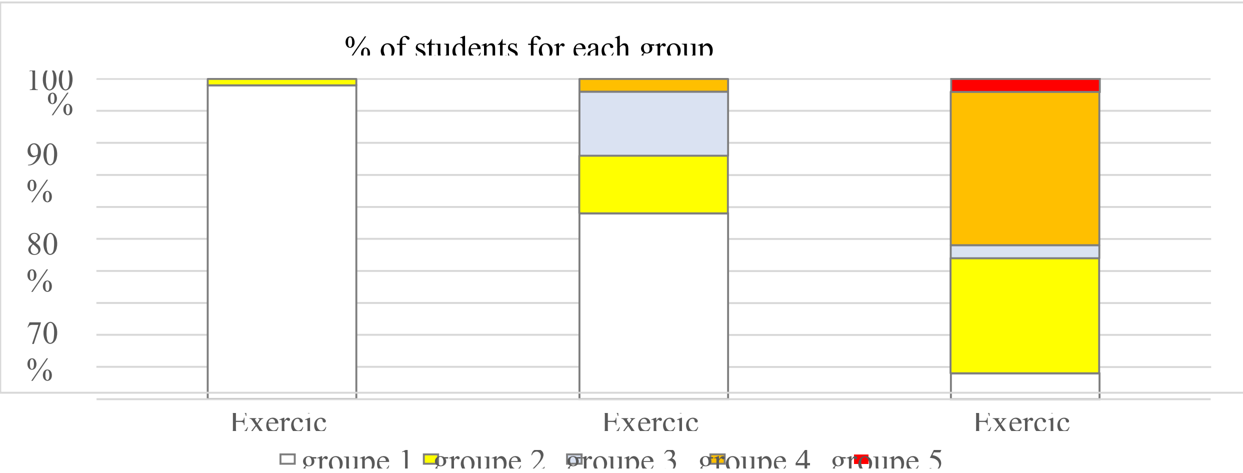


Figure 28. Strategies and time spent of learners in practicing different exercises

The timeline is important to understand how a companion could be designed and useful for learners. It can be used to present whether learners were working on exercises only during face-to-face practical classes time, or whether they were exercising beyond formal classes. When a learner logged in system during the time of class or beyond class, if it was single time or multiple times’ engagement in the date of practical work (TP), or if it was performed on the other dates.

This representation allowed us to observe that the leaners' strategies could be very different depending on the exercises. Exercise 1 was done during face-to-face time in class (except for one person who did his work "late"). 56% of the learners did not come back to work on it without their teacher, in other word, most of them did no engage more efforts on doing the exercise from the different dates of the practical work. Exercise 2 was completed during the face-to-face session on the day of the practical session for more than half of the learners (58%). 18% of the learners posted their work "late" but on the same day of practical session. 20% of the learners posted answers for this exercise both during and outside tutorial hours. Only two learners waited until a different date than the date of TP to post an answer. 30% of learners practiced this exercise on a different day. This suggested that learners focus on exercise 2 on the same day as the tutorial, benefited from having access to it outside of tutorial hours, but that the majority did not continue to practice it on subsequent days. Exercise 3 was only completed during supervision time by just 4 learners. This could indicate that the professor's support time was not sufficient to allow for the completion of all 3 exercises in the classroom. 36% of the learners proposed solutions "late" but on the day of the practical work, and only 2 learners posted answers during and after class time. 48% of the learners did the exercise on a different date, which they would not have been able to do in a "classic" lab. This figure can be read taking into account that the leaners were divided into two groups, that the face-to-face sessions took place in the earlier afternoon and that the second later session ended at 5.30 pm. The possibility of being able to work on the exercises and avoid to complete them on different dates was therefore well exploited, especially for the second group.

To complete this interpretation, we wished to highlight the successes and failures over time of learners deemed to be at difficulty (those who are in difficulty on at least two exercises and they needed at least two attempts in each exercise). We checked the types of errors they made to inference the level of knowledge and prescriptive solutions. This will allow us to determine if these learners have a similar behavior and if they have the possibility of working on the exercises outside of class time.

6.2.8 Learning Registration and Relevant Reflection

Whether learners follow the forgetting curve through spacing effect, memory, and forgetting curves Rao et al., 2023). Whether the theory of Hermann Ebbinghaus applies to specific types of knowledge such as interdisciplinary conceptual and procedural knowledge.

Reflection on learning rationality. Does the learner contribute too much time and effort to learning? In this case, how learners' effort, performance, and efficiency are measured and how they should interact with each other. Appropriate practices may reduce workload, and cognitive load and improve performance for intermediate-level learners.

Learners with different mindsets may have different behavioral and mental training process needs. The amount of time and effort spent by learners may depend on different traits, motivations, and beliefs. For example, learners who have growth-type mindset may prioritize learning goals over achievement goals. They attributed their success to the effort and learning skills. They have the motivation and confidence that learning will affect their cognitive abilities. They can learn from adversity and mistakes, and cumulative learning affects their level of confidence. Fixed-minded learners are likely to prioritize performance over learning. Attribute successes and failures to external learning supports, and external and uncontrollable factors. For example, luck. They may choose to give up learning at times of specific learning difficulties, feeling helpless, stressed, and less confident. Therefore, appropriate learning support and feedback can help them to change their attitudes towards learning.

Furthermore, the validity of the adoption of learning style scales in educational practice has been questioned. This is mainly because learning styles may simply be learning styles that learners are good at and prefer, and these may change as contexts and goals shift. Online interactive learning behavior tracking can detect the efficacy of a learner's more adept learning style and automate formative feedback to improve performance on specific objectives when appropriate. For those learners who have similar cognitive abilities, pedagogical practices should encourage the development of multi-sensory learning opportunities for learners to develop 21st-century competencies. The setting of instructional goals also influences the significance of learning style measures, which can be useful if the goal is to improve individual learning effectiveness, and learning experiences, or to develop a potential for a particular career need. Instruction based on the dual-channel principle and cognitive load theory can be designed to help improve learning effectiveness. Metacognitive adaptive learning systems should be able to recommend learning sequences and provide explicit feedback based on learner's proximal developmental zone. In parallel, it can identify areas where the learner's knowledge and abilities are not mastery and needs the remediation.

The implementation of learning style dimensions and scales and automated learning analytics may help instructional practitioners and learners refencing and modelling adaptive teaching and learning strategies. From certain perspectives, learners' preferred learning attributes are indicated. This may favor learning engagement, success, attraction, self-worth, and active learning. Learners may optimize their learning experience based on their attributes. However, developing activity sequences based on learning styles/preferences should be flexible and adaptable. Fixing learners to a pattern of cognitive, perceptual input, comprehension, and processing learning preferences may affect the development of the learner's professional competence such as the interwoven intelligence, which is needed in STEAM education.

The results found that one group of learners may perform better than another group of learners on a particular content/material. However, this can only show their learning speed and preferred method of learning a specific subject. Therefore, it is stereotypical to assess learning styles for the purposes of education based on individual learning preferences.

Learning styles may also be used as instructional styles. This dimension of learning style is designed to be based on content and objectives. For different subjects, teachers adopt more targeted learning activities that are adapted to changing knowledge and cognitive needs. The categorization of learning styles from the learner's point of view facilitates the exploration of the learner's strengths and vocational preferences, which is only meaningful if the learner is capable of self-assessment and has the capacity for self-regulation.

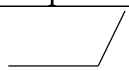
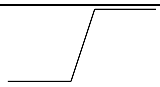
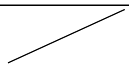
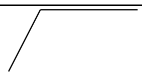
Although experience supports the idea that pedagogical practice using learning styles improves motivation and develops personal traits. The goal of educational practices in higher education shall not be to fulfill specific sensory needs to achieve success. There is considerable evidence to suggest that blended teaching that integrates multiple senses tends to be more effective. This allows learners to store different types of questions and content in their long-term memory. Further evidence is needed that interleaved learning favors long-term memory and improves performance.

Learning styles/preferences based on documented real-time learner behavior may be more accurate. The abilities of learning preferences to influence and improve academic performance depends on the use of big data and artificial intelligence technologies. Although the fact e-portraits have the potential to be labelled, stereotyped, and inaccurate. Learners, educators, and administrators can incorporate the dynamic, timely, adaptive, and adaptable capabilities of e-portraits to optimize learning, provide feedback and advice, present content, formulate plans, decisions, and policies, and develop potentially accurate predictive and early warning systems.

6.2.9 Learners' Profiles and Its Adaptive Learning

We plotted the learners' individual timelines for the three exercises, and grouped them into 7 different profiles. They are summarized in the table and presented in the figures below. The selective profiles of classic leaners can be found from the graphs in the annexes:

Table 16. Learners' Profiles

N° of profile	Description	Exercise 1	Exercise 2	Exercise 3
1		11	10	8
2		11	9	3
3		6	2	6
4		6	2	2
5		5	7	10
6	●	6	13	9
7	Other	4	6	8

We grouped learners into 7 different profiles so as to reflect what is the meaning of deep adaptation, effective learning and how to design adaptive learning.

Profile 1 are those leaners who achieved the first success after several failed attempts and they stopped practicing in the period of our observation, the learning motivation of this type of leaners could be classified as task completion-oriented learners. From the table, it shows that there were 22%, 20%, 16% respectively represented this profile in three different exercises. We primarily identified learners in this profile were those successfully understood the exercises after some practical work. However, it is not easy to know if the success indicated well learners have mastered the required levels of knowledge and skill since they only achieved a first success after several attempts. Moreover, in order to predict the level of mastery and provide the adaptive tutoring and feedback, it seems interesting and useful to detect the errors and the misunderstood of specific knowledge points.

Clarifying whether success was achieved under assistance and guidance of a professor, peer or learning tools could be another indicator of accuracy of learning analytics. Furthermore, whether learners stopped practicing for other reasons such as lack attention, attraction, loss of interest in curriculum, practical work or if they have gained confidence or satisfaction in current outcome and achievement, or preferences in learning new relevant learning content with different activities. To increase learning engagement, learning may be verified through adaptive tests and learning tools for the likelihood of success and the increase of engagement on the basis of providing new testing methods, demonstrations, and problem-solving solutions.

Profile 2 represents learners who were failed after several attempts and continued to try for multiple successful records, this could mean that this group of learners have high learning motivation, engagement, willingness to do more practical work to strengthen memory and verify their reliability and authenticity of success. From the above table, it showed that there were 22%, 18%, 6.25% respectively represented this profile in three different exercises. Learning analytics is able to detect the learner's failures and success, it diagnoses whether the attempts were completed in an intensive rhythm in the class of practical work or on the other days. With the data tracking of the time spent on each attempt, it could inference whether the learner succeeded under the assistance of external and internal feedback. And how the probability of knowledge mastery was calculated and predicted on the basis of performance in different phases. To prevent the cognitive load, adaptive learning analytics may detect repetitive mistakes from learners, inference the causes and diagnose the difficulties in achieving the success. Adaptive tutoring and learning could provide demonstration, personalized hints, feedback, promote learners to try success efficiently, and facilitate them to the next level of knowledge.

Profile 3 represents learners who obtained the first success right after the second attempt but they simultaneously stopped practicing. As can be seen from the table, this is represented by around 12.24 %, 4%, and 12.5% of the three different exercises respectively. For learners who fail and succeed only once, learning analytics can measure and assess the likelihood of mastering based on the time they spent and the mistakes they made during their attempts. Adaptive learning analytics diagnoses whether this type of errors was due to unfamiliarity with the learning software or actual operations. Simultaneously, are learners' successes and failures due to a lack of conceptual, procedural, and metacognitive knowledge? Learning analytics focuses on continuously tracking learners’ performance across different exercises to compare changes in their behavior or knowledge. Adaptive learning may verify the learner's knowledge understanding and mastery and provide further learning scaffolds, such as simplifying or upgrading the difficulty of tasks to promote the needs of individual learning support.

Profile 4 represented the learners who have succeeded after 1 failed attempt and continued to succeed. As can be seen from the table, this is represented by around 12.24 %, 4%, and 4.17% of the three different exercises respectively. Learning analytics could classify this type of leaners as high motivation of success-oriented group. For such type of learner, learning analytics may not focus on the errors they made, instead of this, it inspects how the learner's successful attempts have reinforced the memory curve, cognitive and practical skills., that is, after several successful attempts, did the time required for practices remain consistent, and if persistence improved the learning efficiency? According to the situations and contexts, how adaptive learning analytics provides with different levels of feedback, suggestions and queries to facilitate significant learning. Adaptive learning focuses on reinforcing cognitive flexibility, that is, how to promote deep flexible learning through knowledge transformation and practical scenarios.

Profile 5 represents learners who made multiple attempts with inconsistent results. Learners who consistently fail in their attempts may be classified as at risk or in a difficult group. Learner who always succeeds in his attempts can be considered a well-performing one. As can be seen from the table above, in three different exercises, 10%, 14%, and 20% respectively represented this profile. For those learners in the profile of with learning difficulties. Adaptive learning diagnoses learners' learning difficulties and analyses the causes of misunderstandings and errors based on tracking learning history. Detect emotional factors based on conversation/disclosure analysis and emotional responses through natural language processing technology. Adaptive learning analytics tools can predict understanding and mastery based on question-and-answer sessions in the interactive dialogue. An empathetic, versatile adaptive learning companion or agent that provides tips, relevant materials, suggestions, knowledge points breakdown, simplify tasks, and decomposed steps. Its role may be diverse and include assisting learners develop learning plans, study strategies, note-taking, self-monitoring and metacognitive regulation activities. Adaptive learning mentors can provide demonstrations, explanations, and questions to encourage self-regulated learners to reflect on the causes of errors, adaptive peer collaboration. For learners who are consistently efficient and successful, adaptive learning provides higher-level testing, relevant materials, content and activity sequences. This allows learners to progress to higher levels of knowledge and solve more advanced complex problems. If learners are not able to solve more advanced and complex test content flexibly and effectively, adaptive learning recommends content and activities of appropriate levels but in different forms as practice paths. Adaptive learning may invite learners to participate as experts or collaborators in peer assessment, communication, collaboration, or socially competitive activities. The purpose of adaptability is to integrate learners' expertise and interwoven competences. The open learner model or learning analytics dashboard may visualize learners' optimized learning paths and solutions, which should allow learners to view themselves and provide optimal learning recommendations and suggestions to asynchronous learners. If learner has mastered all the exercises in required level, adaptive learning model may prescribe learning trajectories dynamically visible and transparent, which allow users to draw on the reflection and self-efficacy methods toward learning success. Moreover, system can also invite successful learners to receive badges based on their learning gains, publish results, participate in learning discussions, assessments and games.

Profile 6 represents learners who have done of trying one failure/successful attempt. As can be seen from the figure of table, this is represented in 12%, 26% and 18.75% of the three different exercises respectively. This group could be classified as the least motivated and risk learners. They may be due to not mastering enough knowledge. These types of knowledge may include conceptual knowledge, procedural knowledge, conditional knowledge or metacognitive knowledge. Learning data analysis can be done by looking at the types of errors made by learners and the time spent on them. Infer the reasons for his learning difficulties. However, the difficulty of adaptive assistance and intervention for this type of learners requires more than just remedial solutions for unmastered knowledge points. It also needs to consider the learner's cognitive and metacognitive abilities, such as difficulty level and adaptability issues, learning attitude, learning motivation, concentration level, attention type. Learners may prefer to spend time on reviewing and understanding of other types of learning materials. Alternatively, learners failed in the test may came from other reasons such as the suitability and adaptability of the content. Adaptive instruction may adjust the difficulty level of learning or practice content to provide personalized learning needs. It is worth mentioning that this analysis of learning data was based on a short period of training task, and the evidence obtained deserves teachers, educational practitioners, developers and engineers to reflect on how to carry out feasible, sustainable and targeted computer-assisted learning and programmed instruction.

Profile 7 represents two group of learners, leaners who alternated between repetitive failures and successes during the attempts, or the learners who have never participated or engaged in practical work. We classified them into uncertain groups represented both types of leaners with the characteristics of high learning engagement, initiation or no motivation. As can be seen from the table, this is represented in 8%, 12%, and 16% of the three different exercises respectively.

Learning analysis and evaluation should reflect on whether cognitive, metacognitive methods or personal traits influence motivation, engagement, learning and practicing strategies. These uncertain group may include certain learners who made repetitive or different errors in specific knowledge levels, the data analysis or automatic learning analytics should track and evaluate the types of errors so as to provide the prescriptive analytics. Furthermore, there might be also the group of learners who were motivated in doing more exercises to strengthen memory and to verify the reliability and authenticity of success. Learning analytics techniques should allow detection whether the learner's constant attempts were completed in a specific period of time on the practical work day or on different dates. Based on the observation of time spent and learning registration, it should be able to diagnose the learner's successes were achieved with the assistance of various forms of learning support. Whether the failed attempt was accidental or forgotten, for example, whether the learner has forgotten due to lack of attention to details, cognitive load from increased intensity and frequency of practice, too long interval, etc. The adaptive deep learning system or tool may diagnose the reasons of each learning difficulty and error, predict the occurrence of learning risks, and guide learners to avoid repeating the same mistakes through personalized cognitive analytics. For learners who have the kind of behavior, adaptive learning will provide more auxiliary strategies, metacognitive assistance, and it helps monitoring, planning, and evaluating learners' progress and performance. Guide learners to reflect more on the meta-cognitive strategies, practice until they avoid repeated errors during the attempts in the same unit. For those learners who have never participated or engaged in practical work, learning analysis should benefit from human judgment and intervention.

6.3 Discussion and Conclusion

Instructional design principles are based on the approaches to observe and interpret whether learners' knowledge has changed. The goal was threefold: reflection on the modeling of domain knowledge models, learner models, and adaptive models from data analysis, design principles, standards, techniques, and methods.

Adaptive learning analytics modelling approach can be based on learner interaction, recording of learning process data, static and dynamic analysis, and assessment of explicit and implicit feedback. Explicit data are learners completing online questionnaires, and implicit dynamic data such as learner behavior in online learning activities, e.g., monitoring the number of attempts, time spent on specific exercises or tasks, preferred media, etc., detecting cognitive styles, cognitive abilities, learning strategies (styles), and extracting optimal adaptive methods, techniques and tools from learning resource databases as appropriate, targeting coaching, scaffolding, advising, mentoring, supporting for learning adaptation. In parallel, learning adaptability is meant to enable the traditional collection of more subjective learner data, allowing them to customize personalized learning content, activities, and pathways, and the system is not only based on objective data to recommend adaptive learning. Users can adjust the steps of learning and vote on the effectiveness of the recommended content. From there, the guided learning system recommendation combines a blended adaptive approach, ranging from short-term to long-term adaptations on both small and large scales. Adaptation occurs on a temporary basis and adaptation can be repeated in a long-term and iterative cycle.

We see learner interaction and engagement based on learners' number of attempts. When analysis involves the understand of the difficulty level of the material for the target learners, this type of adaptive approach tends to be taken on a macro scale and employed as a measurement and evaluation criteria of instructional effectiveness, attractiveness and logical feasibility. The micro level of measurement of learning effort, learning achievement, academic success helping the teacher to redesign instructional resources when necessary. The number of attempts, number of successes and failed attempts recorded, memory curves, and learning time spent may reflect on learners' academic performance, practical work behaviors, cognitive changes, reinforcement of memory, deep learning, metacognitive strategies. Instructional practitioners apply standards-based principles to describe learners' cognitive processes, and knowledge acquisition, diagnose learning difficulties and risks, predict probabilities of knowledge acquisition and proficiency, and guide the design of domain knowledge and instruction based on judgments about the validity and the logical feasibility of learning or practices.

The assessment in learning success can be reflected from the mastery level, and failed attempts prior to the first success may reflect learner's understanding of specific problem or conceptual knowledge, and whether or not he or she has acquired sufficient procedural knowledge to achieve a successful manipulation. A higher number of attempts may reflect learner's lack of understanding of content or the learner's motivation to practice. The system is based on learning analytics and data mining to drive adaptive learning remediation, scaffolding, and tutoring to promote effective learning.

Categorizing different learners' portraits facilitates reflection on effective tutoring, coaching, mentoring, recommendations and adaptation methods. In addition to categorizing learners' different learning paths, cognitive processing, the analyses were also directed at integrating some of the phases in which learners had similar difficulties in the attempting process. For example, in the initial attempt stage, where learners in different profiles and made N attempts at the same time, and profile 1 succeeded after their attempts while profile 2 did not, then the adaptive tutoring scheme may be the same for the initial phase before the success. The design principle of the adaptive didactics or instructional model may be to design intelligent tutoring based on the learner's zone of optimal development, recommendation, guidance, feedback, dialogue-based Socratic learning, and experimenting with adaptive learning techniques. For the successful profile of learners, the adaptive mechanism may recommend quizzes, exercises with appropriate level of difficulty, and the system allows learners to perform the reflection activities and self-evaluation by questioning. For unsuccessful learners, the system may provide remediation, demonstrations, explanations, learning suggestions, and help with recall, strategy development, etc., The system facilitates the possibility of deep learning by identifying causes, predicting and analyzing changes in knowledge and behavior, and allowing the learner to explore adaptive approaches. The adaptive features of the system diagnose what has been adapted, what needs to be adapted, where to adapt, when to adapt, and how to adapt.

CHAPTER 7: PROPOSION OF A GENERIC ADAPTIVE LEARNING ECOSYSTEM

7.1 CONCLUSION

This dissertation is one of the few studies to integrate adaptive frameworks and emerging techniques into the adaptive learning environments design, implementation, and evaluation. This concluding chapter summarizes above mentioned-critical contributions, findings, constraints, and challenges before proposing a generic adaptive learning ecosystem for guiding further research and practices. This thesis is the first study to investigate hybrid flexible adaptive learning ecosystem construction in the context of Industry and Society 5.0. With the respect of the integration of relevant theoretical foundations and the incorporation of new technology development trends, it aims to provide evidence and experience based-knowledge and insights for global guidance and strategic decision-making for AI innovation and learning elements transformation. These studies including interpretation of adaptive learning components, mechanisms, features, performance measurement, and impacts evaluation.

The project in this thesis addresses in particular the question of how knowledge circulates in new teaching-learning situations and what roles each of the actors assume. The main work focuses on learning mechanisms, Artificial Intelligence (AI) and Human Intelligence (HI) enabled-adaptive learning environments, which would make it possible to take into account different dimensions and levels of learning science. Adaptive learning design, which should have contained the integration of wide variety of feasible logic teaching and learning principles, emerging technologies in facilitating human -centered adaptive learning ecosystem construction for society. Adaptive learning elements have been influenced and transformed align in these factors. Learning performance and impact assessment focus on highlighting elaboration and identification of crucial adaptive models and relevant parameters. By linking these factors to the specific contexts, the research employs transdisciplinary method, critical synthesis of review, multiple modal learning analytics, evidence-based process mining, and practical experience-based description of overall execution involving key actors participate in the development of system controlled adaptivity, human controlled adaptability-based adaptive learning. With the respect of theoretical evidence and empirical test, these studies derive in common reference frameworks for refining the interpretations, guiding the construction and the evaluation. This should also contribute to the understanding and improvement of adaptive learning impacts in hybrid flexible ecosystem and learning settings.

The comprehensive review of literature aims to develop a didactic engineering framework (Chapter 2), an adaptive learning transformation conceptual framework (Chapter 3), and a taxonomy of learning analytics (Chapter 4). These may help in identifying the logical foundations of learning mechanisms (LM), promoting innovation in AI-enabled learning transformative potential, maximizing learning impacts, improving user experiences, and illustrating current unsolved issues and further challenges regarding the development of artificial intelligence.

7.1.1 Summary

AI innovations enabled the revolutions of education system, these innovations emerged rapidly and unexpectedly ahead of the social awareness, and involved abstract discussions, high-level of employment. However, it remains insufficient analyses and reflection of appropriate construction, stakeholders' involvement, and impact evaluation. This thesis work is undertaken to guide research communities better understand the issues, logically analyze potential impacts, and effectively formulate relevant measures. A variety of reactions have been taken by stakeholders to analyze complex interactions between technological options, feasible solutions, and adaptive environments construction in Higher Education Institutions (HEIs). However, a more inclusive conversation and collaboration among Governments, Organizations, HEIs, vendors, domain knowledge experts, teachers, learning practitioners, and researchers, is still needed to clarify the minimal requirements in knowledge productions for Adaptive Learning Environments (ALEs) integration in Adaptive Learning Ecosystem (ALE). Indeed, there is increasing ambiguity and design concern in the issues of integration, innovation and evaluation of AI-enabled adaptive education. This generate the research gap and leads to key research question: what does the main steps in designing truly promising successful ALE?

This dissertation contributes to these efforts by establishing a set of propositions for designing Adaptive Learning Environments (ALEs) within different contexts. The main research question that guided this study is as follows: how should adaptive learning environments implementation can be integrated into construction and development of Adaptive Learning Ecosystem (ALE)? To address the main research question, first reviewed the literature on adaptive learning systems to understand the research contribution to the topic and define the scope of this study (Chapter 1). Despite, a wide range of propositions in improving learning outcomes focus on the investigation of theoretical foundations and classic didactic triangle. The author reviewed historical literature, identified newly design issues and relevant concerns due to the limitations of traditional didactic design and adaptive approaches. The author of this thesis found that there is a lack of supportive propositions and guidelines to explain the acquisition of different types of knowledge, logical learning mechanisms and feasible intelligent features enriched learning environments in facilitating (meta) cognitive processes, therefore, we develop a comprehensive didactic framework align with adaptive learning science (Chapter 2). Furthermore, there is a lack of interpretations of adaptive learning system' evolutions, significant learning transformation, impacts evaluation, and preliminary evidence and propositions for the design of ALE (Chapter 3). As we have highlighted in Chapter 3, we developed the propositions align with different contexts, diverse requirements of actors, specific measurement indicators for addressing unique needs, and evaluating learning effects and quality. The propositions can be used to guide specific project implementation that can be distinctive or comparable in terms of goals, contexts, mechanisms and technologies. It enables the development and the evaluation of actual interplay in learning elements within ALE. A taxonomy based on several LA approaches and EDM parameters are formulated and proposed in Chapter 4, since the adaptation can be based on single variable or in combination with several factors. These parameters could be divided into the categories according to specific factors. These evidence-based proposals or principles for improving adaptive learning design to enhance the construction and impacts of ALE, would allow researchers, designers, and practitioners to gain the insights on the feasible design, comparable, viable implementation strategies, cost-effective evaluation and further adaptive intervention measures.

Building on these proposed frameworks and classification systems, it is now possible to theorize about how different technologies embeddings of the still new field of ALE in education affect learning outcomes in different pedagogical scenarios and didactic sequences. To repeat, this investigation develops propositions that aim to facilitate knowledge production and circulations in new teaching-learning environments or circumstances underpinned by robust theoretical foundations, empirical testing of requirements, and learning evaluation for recommendations into future new adaptive learning principles for ALE.

These studies contribute to the ALE design based on the interpretive approach, comprehensive and critical synthesis of review to ensure precision education with a transdisciplinary method. This study provides practitioners, researchers, policy makers, with needs and inspirations to design ALE and help them ensure that user manipulation are based on such dynamic process and trustful mechanisms. Especially as human-machine interaction technologies continue to advance, the knowledge of design logics based on the perspectives of neuroscience, cognitive psychology, social culture might encourage designers and research towards a more sustainable design of these novel.

7.2 Discussion of Contributions And Implications

This dissertation investigates and establishes a set of proposed frameworks and taxonomies of learning mechanisms (LMs), artificial intelligent enabled-adaptive learning systems (AI-ALS), learning analytics (LA) to enhance the construction, implementation and evaluation of adaptive learning environments (ALEs).
Going further, the following subchapters would provide the critical insights, based on these research efforts, and explain their relevant impacts and contributions in charting a globally generic adaptive learning ecosystem (ALE) framework. This framework aims to offer comprehensive visions by elucidating reference models and adaptive mechanisms, to further understand mediating tools, in the regard of enhancement of entire learning management, teaching, learning and evaluation processes in authentic HEIs.

7.2.1 Contributions Within the Contexts

As it is detailed in Chapter 1, a wide range of so-called intelligent tutoring and adaptive learning systems design that presented in the existing reviews, have been doubted by their limited effectiveness and capacities of compatibilities, adaptivity and adaptability. This is mainly due to ineffective adaptation and insufficient integration, based on adaptive parameters, multiple-dimensions and models. Systems that incorporated the adaptation elements into classic reference models without effective evaluation and transformation may lead to poor performance, and implementation challenges in generating positive outcomes. Indeed, it has been underscored that education and knowledge systems often face difficulties and challenges to adapt in changing needs of curriculum, pedagogy, diverse learner types, and increasing demands in adaptive professional development and expertise integration. Thus, more research and investigation are expected, especially in multidisciplinary knowledge integration, comprehensive evaluation with interdisciplinary intelligence, transdisciplinary research and careful planning on feasible design, testing of learning variables and didactic priorities. These conducted initiatives or solutions should enable the education sector to effectively maximize the impacts of learning (performance and quality) by science of adaptive learning, learning analytics, and logically minimize the potential risks that influenced by AI technological revolutions.

A didactic framework is elucidated in Chapter 2, which involves the explanation of learning mechanisms (LMs) that facilitate the construction of cognitive schemata, the acquisition of knowledge components, the diverse design features of intelligent adaptive learning environments. The idea is to explain the important adaptation by the approach of (meta) cognitive processes. To be more specific, how learners learn and instructors teach with appropriate methods. Overall, the propositions offer design guidance and cognitive map for didactic engineering innovation, and integration of learning mechanisms in hybrid learning scenarios for enhancing the computability, adaptivity and adaptability of ALE.

The adaptive learning conceptual framework is proposed in Chapter 3, which illustrates the importance of appropriate systems' design, according to specific theories, technologies, strategies, approaches, tools, and techniques in multiple-elements and dimensions of models' construction and systems' optimizations. The idea is to reveal the importance of conception, transformation, and evaluation of significant learning. Furthermore, how the education sector leverages these components and incorporate adaptive technologies to reduce the transformative potentials and maximize learning impacts. In general, the propositions provide a common reference and mind map for adaptive learning system' revolutions by examining specific adaptive learning innovation especially extending learning analytics scales, increasing deeper learning approaches to facilitate self-efficacy, adaptive -collaboration and socially shared-open learning in the context of co-value created ALE.

A taxonomy of learning analytics (LA) is proposed in Chapter 4, which aims to offer diverse evidences, specific insights for adaptive learning research communities and practitioners to understand adaptive learning process, the optimization of adaptive techniques and adaptive resources according to knowledge goals, user's profiles, learning innovation solutions. By integrating the evidence and experience, learning analytics (LA) combine learning metrics and criteria with Educational Data Mining (EDM) techniques to describe, predict, diagnose, inference or prescript adaptive factors and parameters (i.e., performance, interactive behavior, (meta) cognitive status, personal traits, learning strategies, emotional states, user satisfaction, learning difficulties and expectation). These measurements and evaluation results contribute to provide proposals that contain adaptive learning elements for precision adaptive deep learning system by leveraging the impacts and potentials of AI and LA, and enhancing learning outcomes. Moreover, the proposition of multimodal LA aims to support the further incorporation of optimized (embodied) pedagogical agent system such as synthetic agent system or metacognitive tutor in the context of ALE to realize multimodal learning activities, adaptive intervention and customized adjustments.

Chapter 5 elucidates the context and blueprint of project, and specific issues to understand, and potential challenges to address. It aims to present how adaptive education system experts, adaptive learning practitioners and scientists combine prior knowledge and experience to design automatic solutions and technologies adapted to teaching requirements, according to the protocol goals, measurement criteria and adaptive indicators. The goals can be diverse and specific according to the modules, such as development of automatic evaluation and feedback system to further improve teaching, learning and evaluation design.

Chapter 6 formulates implementation strategies to develop automated evaluation and feedback tools to promote personalized learning or autonomy learning. Throughout the support of learning companion application, learning trajectories and progress in the interactive platforms can be recorded by invisibly data tracking. Automatic learning analytics enables to provide the grading and feedback. The pilot test and data analysis offer the evidence and experience to designers, researchers, engineers, educators, and policymakers to question innovative solutions and reflect on the strategies or regulations for the next adaptive learning environment design.

Thus, the major contribution of dissertation is to identify the theoretical foundations, to propose the frameworks and taxonomy that provide guidance, reference, and solutions for addressing the diverse issues, specific needs, minimizing the challenges of innovative system transformation and enrich the features of ALE.

7.2.2 Providing Insights Considering Implications for Adaptive Learning Ecosystem

As highlighted in Chapter 1, the critical aspects in developing adaptive learning should integrate technological innovation with appropriate theoretical models and frameworks; and the effective evaluation of adaptive learning solutions can be overlooked in experimental investigation.

Currently, there is a paucity of a framework to guide the understanding of the construction and impacts evaluation priorities and of Adaptive Learning Ecosystem (ALE). Concerning this, we draw on the highlights, as well as critical points for evidence-based framework in the creation and implementation of hybrid flexible adaptive learning environment in Chapter 2. The objective is to further investigate and test multiple-factors as mediating tools for inclusive adaptive learning ecosystem design.

Adaptive didactic engineering and transformed adaptive learning models are proposed respectively in Chapter 2 and Chapter 3, and they are identified as appropriate for guiding the design of relevant components, mechanisms, and systems in terms of models, features and functionals that should be incorporated in the generic adaptive learning ecosystem (ALE). Chapter 2 focuses on the elucidation of the specific interplay among domain knowledge components, learning mechanisms, adaptive instruction and learning environments, to understand the whole picture and particular needs of learning contexts and (meta) cognitive tools construction.

Chapter 3 argued that integrating adaptive theoretical foundations into an adaptive learning conceptual framework can be appropriate to verify logic feasibility of technological innovation, and systems revolution relies on the optimization of models, techniques, tools and methods to improve the implementation impacts. As detailed in the Chapters, AI-ALE can be a more advanced and inclusive form of adaptive learning system. ALEs can contain various learning systems (e.g., ALP, ALS, ITS, dialogue-based ITS, AI-ALS, LA-ALS, and exploratory learning environments). AI-ALE are dynamic, as they continuously integrate the evidence and feedbacks from human-machine interactions, to optimize models' construction, enrich intelligent system, diversify knowledge system, adaption engine, and intervention mechanisms. Chapter 3 reveal that learning through ALE should fit users' schedules, and provide hybrid, flexible, adaptive learning and feedback loop for each sector or individual, thus, allowing them to craft their teaching, learning or assessment plans. The different approaches learning stakeholders use to appropriate content and how these strategies change as skills develop are important. As detailed in Chapter 3, the capabilities of intelligent adaptive learning system can be characterized by providing optimized learning, dynamic evaluation, adjustable mechanisms, adaptive feedback and personalized support. Thus, we conjectured that intelligent tutoring, adaptive recommendation, synthetic agents, personalized learning, adaptive intervention mechanisms would be the core elements to improve construction of efficacy learning and feedback loops in ALE.

As described throughout Chapter 2, Chapter 3, and Chapter 4, learning mechanisms, artificial intelligence, and learning analytics play major roles in constructing hybrid flexible, as well as personalized adaptive learning environments. The evaluation of learning impacts, based on the development of emerging generative artificial intelligent models, and adaptive learning technologies, should look at the criteria of logical feasibility and sustainability in transforming the technological implications and potentials to the knowledge circulations and co-created human values impacts.

As mentioned in Chapter 4, LA assesses each learner's prior knowledge, cognitive status, as well as affective, behavioral, motivational states, and metacognitive strategies, based on learner's interaction with learning environments to improve adaptive system's performance and learning experience (Ofelia San Pedro and Baker, 2021). A multimodal learning analytics should be considered in the evaluation of ALE. The analytics of performance should assist the design of personalized interactive systems. The analytics of behaviors plays a major role by holding that LA-ALS should describe learners' data, capture logs of learners' activities, analyze, plan, and provide actionable insights, and thus help predict adaptive learning activities. The analytics of cognitive states, learning preferences, and emotional states are important to user satisfaction, as they can influence the learning strategies and user experience. The evaluation of technology acceptance is relevant for user experience and as it underscores usability, utility, flexibility, and adaptability of a system. The analytics of learning difficulties or risks in dropping-out is relevant, as the information obtained from the early warning model (which detects at-risk learners) can influence the design of scaffolding activities and feedback loops that will be provided to a given learner to improve learning outcome. Because scaffolding helps learners with solving problems, and they will need feedback on their learning progress. Thus, adaptive learning analytics and effective intervention mechanisms, automatic evaluation tools should be considered in the design of ALE, it emphasizes that AI and LA enabled-ALEs must provide the optimal adaptive learning support to a specific needs of learning practitioners in different situations. For instance, learners in learning risks may get different types of feedback throughout the whole learning process, and as personalized as possible. Thus, we conjectured that capability of adaptivity, learners' interests, motivation, emotional needs, learning preferences, learning effects, learning adaptability, technology acceptance, learning engagement are all relevant to improve performance and user experience of ALE.

As discussed above, ALE is designed to dynamically adjust to the types of learning goals according to learner's abilities or skill attainment in ways of automated evaluation and intervention that accelerate individual performance. New approaches of diagnostic and formative assessments with AI adaptive deep learning technologies are gaining the interests of education sectors. These neural network techniques should empower and renew LM+AI+LA principles and solutions to drive the capabilities of ALE.

Chapter 5 presents project background, describes the protocol for designing adaptive learning environment according to the context. The identified propositions showcase the capabilities of adaptive learning systems can provide learners with emotional detections, meta cognitive scaffolding, tasks-corrective feedback to improve self-efficacy learning during practical works. Personalized learning mechanisms could be correctly identified and gradually developed to minimize cognitive loads and to maximize learning efficiency. PIALS can automatically assess learners' level of knowledge, guiding them to progress and adapt efficiently and effectively. The automated formative and summative assessments, personalized and adaptive feedbacks, emphasize the approaches in improving learning effects and quality within the personalized learning mechanisms.

Chapter 6 elucidates the concept of continuous feedback loops and assessments that can be developed, based on how learners completing their tasks, what adaptive feedbacks they should receive to adjust their actions accordingly (Khosravi et al., 2020). Each time the system offers the feedback, and the learner makes corrections, new feedbacks are required (Khosravi et al., 2020). This cyclical and recursive evaluation and feedback loops reaches the end until learner mastering the knowledge goals. The integration with ALM, GAI and ALA techniques becomes necessary in the provision of personalized, intelligent, adaptive learning, and timely, ongoing resources recommendations, individual learning support.

7.2.3 Reflecting Adaptive Learning Way Forward

As stated in the Chapter 1, classic systems and models are reviewed to understand diverse models, learning mechanisms, artificial intelligent and emerging technologies, learning analytics, (meta) scaffolding support. These serve as the mediating tools for adaptive learning. This thesis study is also concerned with exploring or testing the theoretical relationships among the elements with an interpretive approach and transdisciplinary knowledge.

The objective is to explore how LM, AI, LA can be used to enable a hybrid flexible, intelligent personalized adaptive learning. Thus, the positioning indicates the relevant impacts of these propositions as they depict certain features and functions that are significant in specific ALEs for the use in real educational settings. For instance, in Chapter 2, use-centered adaptive learning mechanisms and Chapter 3, recommendation and adaptation engine are positioned in adaptive models and learning method structures due to their influences in the human-machine interactions. Since learners learn with platforms or applications, both of these adaptive learning mechanisms and recommendation engines ensure that systems or applications continuously learn from human input, as well as improve effectively learning experience.

This thesis underscores the significant roles of LM, AI, LA for addressing needs of adaptive learning construction, the individual learning, adaptive protocols, metacognition intervention, and auxiliary models developed by experts (e.g., involve educators, designers, developers and learners) for co-designing an advanced ecosystem, along with co-creating users' goals of values. The propositions are not to replace or to be compared with the traditional methods or models, as they do not detail relations among the mentioned concepts or components.

LM+AI+LA driven adaptive learning and system construction by intelligent techniques (e.g., curriculum sequencing (also referred to as instructional planning technology). This method can provide the learners with the adaptive sequences or paths of knowledge units to learn which is best suited to their learning goals and current level of knowledge (Martin et al., 2021). It can also plan the activities of learning tasks (examples, questions, assignments). Adaptive learning system can determine what learners know and to move them feasibly and appropriately through a sequential learning path to prescribed learning goals and skill mastery. These systems that characterized with the techniques of AI and LA to achieve this aim by overcoming learning challenges (e.g., varying learners' learning abilities, diverse learner backgrounds, and resource limitations). Specific Adaptive Learning Mechanisms (ALA), features and functions of adaptive and adaptable systems that have been identified in the literature and these findings (e.g., effective sequential learning paths to prescribed learning outcomes and skill development) will lead to better course progression and outcomes. These evidences build up the frameworks and taxonomy of learning analytics, which can support the intentions of LM+AI+LA driven adaptive learning systems to assist learners in acquiring knowledge and skills in a particular sphere using various theoretical foundations, adaptive models and learning techniques. The learning processes in adaptive learning systems are influenced by process scaffolds, which may combine with learners' aptitudes. (Meta) scaffolding activities take various forms depending on learners' needs: models, cues, prompts, hints, partial solutions, think-aloud modeling, and direct instruction. These scaffolds help learners solve problems, carry out tasks, master concepts and achieve goals. Scaffolding, especially meta-cognitive auxiliary underpinned by neuroscience enriched learning analytics, significantly transforming adaptive learning activities and stakeholders' roles and involvement. For instance, it facilitates educators to design didactic engineering and pedagogical activities. These include adaptive hypermedia with optimized adaptive learning materials, adaptive instruction with fewer shot learning, intelligent tutoring with personalized tutors, synthetic agent' system with optimized learning support, multimodal learning analytics and personalized evaluation enhanced adaptive learning systems to increase learning performance. Thus, these well-designed adaptive technologies by the efforts of joint actions of didactic engineering behind multiples-disciplinary knowledge-based evidence, interdisciplinary intelligence-based practices and transdisciplinary evaluation approaches-based experience, enhance adaptive learning performance. By different levels of interaction and involvement, learners are able to gain insights to construct adaptive change in the virtual learning environments, and therefore, they can be more active, autonomy, and self-efficient (Vermunt, 1996; Matsuda et al., 2020; Miedijensky, 2023).

7.2.4 Research Endeavors for Addressing Needs

In despite of increasing interest in developing precision learning and personalized adaptive environments, there remains an ambiguity issue to which cause-effects of learning. The challenges of integrating valuable resources, knowledge for evaluation led to concerns, urgent needs of regulations, and a balance between relevant indicators and implications. The main research requirements that guide this investigation is as follows: how a dynamic adaptive learning ecosystem should be constructed and developed?

To address the investigation requirements in this field, Chapter 2 conducts a comprehensive review, which aims to present adaptive learning theoretical foundations, design concerns and instructional practices. Chapter 2 elucidates a comprehensive didactic framework that can guide effective instructional practices in adaptive learning environment. The efforts made are based on considering design issues and concerns that generated by influential technological breakthroughs and revolutions, with increasing demands of adaptive expertise reskilling and higher-order skills upskilling, diverse socio-cultural collaboration activities and co-creation of human values. It aims to propose a reference guideline, which emphasizes the interdisciplinary approaches and framework's applicability across diverse contexts, knowledge goals, adaptive technologies, highlighting its versality for promoting precision learning and addressing the unique needs of different settings in intelligent adaptive education. Built on different contextual models, educational theories and learning science foundations, this chapter explains how to develop adaptive solutions that can improve didactics, pedagogical adjustments, increase learners' engagement, optimize learning sequences, activate interactive mechanisms, deepen learners' cognitive construction processes, enhance adaptive expertise integration. This contributes to provide the valuable insights to the adaptive learning science research field, offering the foundations for further investigations, and reinforcing the adaptive learning science significance in the dynamic interactive learning mechanisms' design and development landscape of diffracted instructions and adaptive learning environments.

Chapter 3 employs a synthesis of review method to sort out the interpretations of adaptive learning, which aims to interpret the contexts and current specific issues. It elaborates the illustrations and refinement of adaptive learning conceptual framework in the context of society 5, focusing on its transformative impacts on the revolutions of adaptive models, adaptive learning practices, technological integration, and improvement of overall performance and quality of learning. It contributes the valuable insights to the adaptive learning system research field, offering the foundations for further investigations, and reinforcing the adaptive learning system framework's significance in the dynamic construction and evaluation landscape of hybrid flexible management, intelligent tutoring and adaptive learning ecosystem.

In Chapter 4, the features of learning analytics and educational data mining are analyzed, and their corresponding functions in relevant evaluation models and techniques are presented. The comprehensive reviews in this Chapter enable to create a taxonomy of learning analytics and to propose a multimodal adaptation mechanism, based on educational data mining and machine learning techniques, focusing on addressing the needs in the measurement, evaluation and intervention, based on diverse adaptive criteria, indicators, parameters. These evidences should enhance the capacities of educators, engineers, developers, and data scientists for the decisions-making in improving teaching management, personalized support, intervention approaches and feedback loops design in personalized, intelligent adaptive learning environments. The investigation in Chapter 4 contributes the valuable insights to the adaptive learning analytic research field, offering the foundations for further investigations, and reinforcing the adaptive learning analytics taxonomy's significance in the dynamic evaluation and design landscape of didactics, personalized learning and cyclic feedback loops. Eventually, a reference framework of multimodal learning analytics is proposed, which allows the researchers and educational practitioners and learning analytics communities to design, evaluate specific systems techniques employed and impacts in targeted projects.

On the basis of theoretical evidence and research efforts, it is expected that the subsequent research and relevant project can be developed under these critical reflections to realize the full potential of intelligent adaptive learning technologies in facilitating learning performance and educational quality in different pedagogical scenarios, learning circumstances and assignments.

Chapter 5 describes ET-LIOS project, which aims to implement hybrid training and to conduct experiments in different modules' pilot tests (e.g., measuring learning impacts in terms of performance and quality). It proposes the recommendation and reference into construction principles and elements of personalized intelligent adaptive learning environments. Especially when artificial intelligence, machine learning, deep learning techniques continue to develop, relevant knowledge and constraints of their implementation in adaptive learning construction are expected to benefit the stakeholders in this domain. It presents the context of project, and the joint creation-protocol for designing a learning companion to enable automatic evaluation and feedback. It offers the evidence and experience to the future adaptive learning programs in the fields, offering the foundations for further investigations, and reinforcing the targeted adaptive learning program's significance in the dynamic policy-making and design adjustment landscape of specific project.

Chapter 6 describes the collection and analytics of learning data from module D, which focuses on two key measurement criteria (e.g., learning performance and quality). The descriptive analytics of performance, interactive behaviors, learning progress, cognitive strategies, possibility of knowledge mastery and learning difficulties, provide learning evidence to further improve further curriculum design and applications' integration. The results described in Chapter 6 offers the evidence and experience in personalized intelligent adaptive learning companion system research field, proposing the foundations for further investigations, and reinforcing the adaptive learning companion's significance in the dynamic evaluation and design landscape of didactics, personalized learning and cyclic feedback loops. This chapter observes and interprets learning results, which should be useful to generate deeper insights into the design principle of user-centric adaptive learning in the context, and to present the evaluation results and experience that can improve teaching management, user satisfaction and learning experience.

The conclusion of the construction and impacts of Adaptive Learning Ecosystem (ALE) are summarized in the following chapters. These should contribute to the comprehensive understanding of ALE, knowledge transfer and human co-created efforts for reframing AL definition, and examination of present research insufficiencies and future opportunities.

7.3 PROPOSITION OF A GENERIC FRAMEWORK

Despite the emerging intelligent adaptive learning models and (embodied) (meta) (cognitive) synthetic agents are characterized with the capacities in revolutionizing adaptive technologies and optimizing adaptive learning sequences activities. Certain intelligent adaptive technologies have been questioned in the capacity of underpinning meaningful learning. For instance, the intelligent personalized applications, based on the employment of large language models, generative AI to develop human-machine co-created activities, dynamic interactive-reflective feedbacks. And the complexity in implementing optimized, deep learning, adaptive testing technologies, which accurately describe, diagnose and predict levels of learning, appropriately recommend adaptive activities, automatically detect learning misconceptions or difficulties, and ease to adjust sequences of curriculum and learning paths (Taub & Azevedo, 2019).

ALEs support the proliferation of adaptive methods, techniques, and tools provisions. Former developed chapters have elucidated the logically feasible mediation of adaptive learning relies on the feature engineering, diversify knowledge systems and adaptive learning mechanisms enriched from learners' models, domain knowledge models, management models, pedagogical models, open learning and adaptive models (see chapter 3, and chapter 5). The ecosystem should enhance adaptive learning policy-making, effective didactics, instructional principles, and learning practices related to develop adaptive self-regulated, co-regulated and socially -share learning activities (Yu, 2023; S.-H. Jin et al., 2023; Feraco et al., 2023).

Generic framework is distinctive by its robust logic evaluation of versatile design, innovative approaches, feasible impacts, derived from the foundations and evidence in adaptive learning science, various technological innovations and human needs. It explores the construction and development of ALE in higher education institutions (HEIs), it contributes to the conceptual understanding and specific implementation impacts in hybrid learning and training settings.

7.3.1 Objectives and Significance Overview

The objective of this thesis is to question digital environments for teaching and learning during the design phases, to test their robustness during their use in situ, and to measure and evaluate the impacts on learning. This research work should make it possible to understand different learning aspects and improve educational practices by relying on a solidly supported body of knowledge. This chapter specifically explores the application of an adaptive learning ecosystem in Education 4.0 paradigm and new ideas for design under the vision of Society 5.0.

The literature review and empirical work carried out in this thesis contributed to designing an innovative hybrid flexible adaptive learning environment to adapt to the differentiated needs of learners to achieve the targeted educational objectives. The empirical work in the design stage will make it possible to produce devices that allow the automatic capture of learners' traces. Secondly, the evaluation stage consisted the investigations of didactic uses and verifications of adaptive learning sciences. The proposed methodology of assessing the environmental impacts of innovative learning relied on theoretical models, adaptive methods, techniques and tools for collecting digital traces to exploit and analyze learning scenarios. Thus, qualitative and quantitative analyses of student traces (learning analytics) make it possible to detail the different strategies used in this educational environment and to generate patterns (Process Mining).

The results of this research are to reveal the functions of the didactic system observed, and in particular, the differential forms that govern the learning trajectories, which are always singular. The main objective of the chapter is to design an ecosystem framework for the integration of adaptive learning environments, analyze the coordination and cooperation among stakeholders in the implementation of educational innovation, and how educators can correctly choose appropriate instructional principles, pedagogy activities, and monitoring mechanisms to enable learners to adapt to the new learning environment and develop their adaptive expertise. Another significance of the thesis is to complement the research on the triangular relationship of didactics, including epistemology, the interrelationship among human teachers, virtual tutors, companions, learners, and their changing roles in adaptive learning environments.

In this context, this chapter aims to develop a polyhedron framework of an adaptive learning ecosystem, and elucidate research gaps in the current literature. Chapter 2 mentioned that there remain research insufficiencies in achieving higher level of success in the transformation of adaptive learning: the complexity in the optimization of adaptive and adaptable learning mechanisms to improve learning effects; the paucities of adaptive learning systems that facilitate higher-order skills acquisition in trans-disciplinary approaches; the necessity of constructing (meta) cognitive tools with learning analytics and deep learning technologies; the opportunities in the construction and evaluation of generative AI in the ecosystem by transdisciplinary intelligence and human collaborative values from stakeholders' involvement.

To improve the performance and enhance the effects, this study underscores the significance of proposing a generic framework for developing a dynamic adaptive learning ecosystem, which enhances compatibilities, adaptivity, and user-controlled adaptability for promoting higher-level of adaptation, higher-order skills acquisition and user experience; creating a hybrid flexible learning environment and mechanism that enable the collection of explicit and implicit feedbacks for the adaptation by human-machine interactions and transdisciplinary collaboration; reflecting on the construction and impacts of adaptive learning environments, and their relevant approaches, techniques, tools, emphasizing the significance of personalized adaptive learning analytics model, metacognitive auxiliary model and intervention mechanisms in facilitating the personalized deep adaptive learning process; creating a taxonomy of learning analytics approaches and data mining techniques that provide a common standard reference for stakeholders to select appropriate adaptation indicators, elements, parameters, or methods for co-creation of intelligent adaptive learning and feedback loops in ecosystem (i.e., higher-education institutions).

By combining didactic framework we developed in Chapter 2, which is based on the studies of learning theoretical foundations, instructional principles, adaptive learning mechanisms; Chapter 3 mentioned the importance in classifying theoretical foundations, adaptive learning practices, adaptive learning models, systems revolutions techniques, and transformative impacts; and the evaluation realized by learning analytics and educational data mining in Chapter 4, field experts should be able to leverage these evidence, elements and principles to appropriately construct adaptive learning ecosystem and evaluate learning effects in different contexts and specific projects.

7.3.2 Adaptive Learning Ecosystem Construction

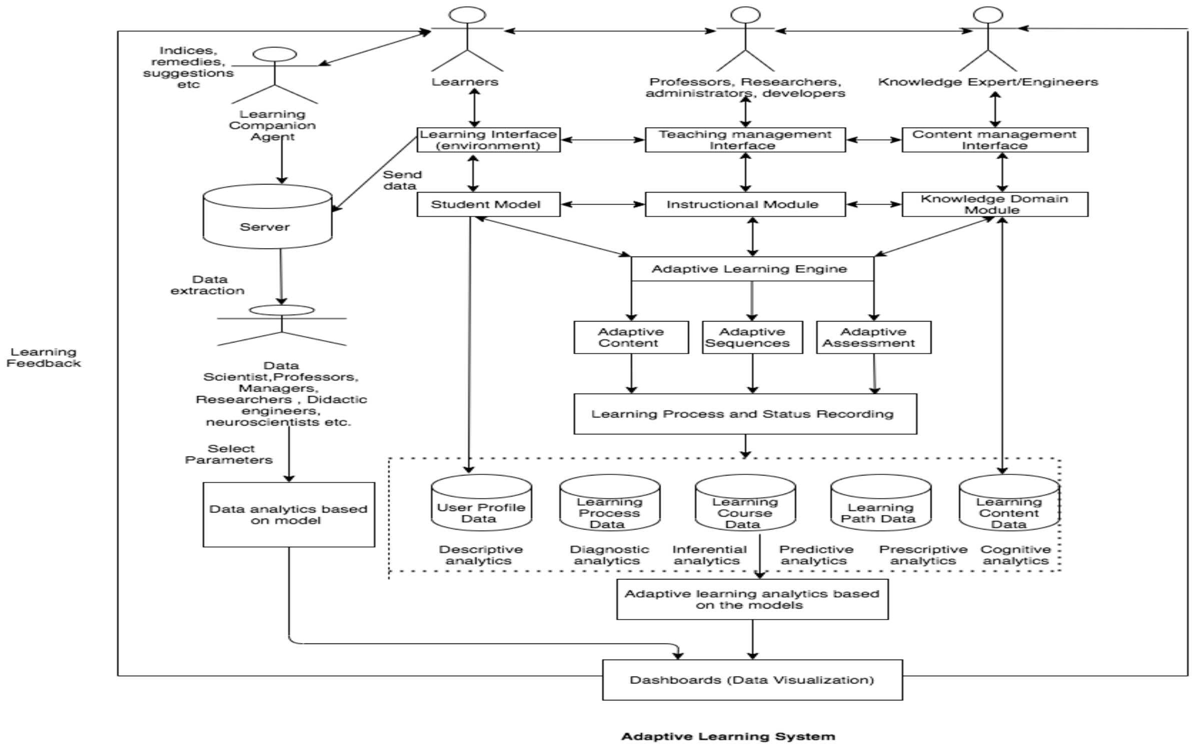


Figure 29. Adaptive learning ecosystem framework

Figure 30 illustrate stakeholders' involvement in adaptive learning ecosystem construction and impacts evaluation, which present the detailed elucidation of engaging interactive systems, specific models, and the interpretation of adaptive techniques in diverse contexts.

As mentioned in chapters 2, 3, and 5, the dimension of domain knowledge model construction concerns how educators and curriculum innovation experts design knowledge graphs, or cognitive maps according to types of subjects and levels of learners' knowledge. And, how they leverage theories of semiotics, information processing, gestalt, law of effects, neuroscience, to diversify learning content, develop intelligent textbooks or ongoing learning resources, and enrich adaptive hypermedia, instructions or optimize personalized adaptive learning and cognitive processes.

The dimension of didactic model construction concerns in how educators, didactic engineers, pedagogy innovation, or adaptive learning experts design instructional principles, didactic strategies, monitoring, evaluation, and feedback mechanisms according to semiotic theory, behaviorism, and cognitivism. How they employ logically feasible construction of external adaptive learning activities or practices, and internal cognitive mechanisms that foster cognitive flexibility, minimize cognitive load, and therefore, enhance cost-effective of sustained methods.

As mentioned in chapters 3 and 5, the dimension of user model construction concerns in how adaptive learning stakeholders, and beneficiaries, build learners' profiles by dynamic and static methods to collect explicit and implicit information and feedback. Various modeling techniques (i.e., overlay model, and Bayesian network), enable educators and learning analysts to effectively classify learners' types, learning interests, and levels of performance, and to understand learning difficulties or misconceptions. Adaptive learning practitioners employ algorithms and machine learning techniques as didactic tools to construct learning support and intervention mechanisms.

As mentioned in chapters 2, 3, and 5, the dimensions of open learner models and learning models have become critical approaches in encouraging adaptive self-regulation, peer learning, peer evaluation, co-regulative and adaptive socially-shared strategies that combine with self-efficacy theory, social-cultural constructivism, connectivism, generative theory of open AI.

As mentioned in chapters 2, 3, and 5, adaptive learning mechanism, engine, or adaptive interactive model, which is like the "brain" of adaptive learning, it concerns in how practitioners (e.g., machine learning engineers, developers, and cognitive neuroscientists) combine advanced intelligent techniques with embodied cognition, multiple disciplines' intelligence, generative AI, artificial neuro networks to recommend user-oriented optimal adaptive learning resources, content, sequences, assessments.

As mentioned in chapters 2, 3, 4, and 5, the dimensions of personalized adaptive learning analytics models, metacognitive auxiliary models, bio or neuro adaptive feedbacks, and intervention mechanisms construction have become influential adaptive factors in enhancing meta-cognitive systems development that combined generative multiple intelligence, theories of proximal zone of learning and metacognition to support precision learning, facilitate deeper learning, self-reflective and evaluation activities.

The designed generic architecture elucidates how the field or domain experts integrate adaptive learning science and feasible technologies for significant learning construction and evaluation. With the employment of theoretical foundations, adaptive models, diverse types of learners and levels in domain-general knowledge or individual-specific knowledge, the capabilities of adaptivity and adaptability could be enhanced by the effective incorporation of didactic design, differentiated instruction, intelligent adaptive learning techniques, customized individual learning methods.

This generic framework aims to suggest adaptive learning research communities, pedagogy innovation experts, educational practitioners in what intelligent adaptive techniques, knowledge graphs, learning sequences, assessment, and learning companions, when these should be appropriately incorporated in teaching diverse subject areas? Which and why the didactic activities should be designed logically (e.g., conversational, dialogue-based, step-by-step, discovery, or exploratory)? How to implement efficient tutoring, coaching programs, feasible diagnostic assessment, and feedback tools according to learner's knowledge types, cognitive abilities, emotional status, physiological and psychological signals? Where and when task-specific information or adaptive feedback could be embedded into systems to assist precisely the acquisition process of specific knowledge component? And what and which ongoing learning resources and materials (e.g., text, images, cross-exercises, and videos) and learning support (e.g., automatic detection of learners' profiles, intelligent credit tables, deep learning analytics dashboards, and learning management mechanisms), can more effectively and viably assist in the facilitation of cognitive processes, metacognitive flexibility and neuro sustainability.

Despite previous reviews reveal that certain range of systems enable users to participate in interactive and self-reflection activities to support the construction of adaptive learning and feedback loops. A wide range of these systems lack of more verifications of adaptive techniques underpinned by adaptive learning science (e.g., adaptive learning theories, deep learning analytics, cognitive neuro science). For instance, what feasibly effective adaptive assessments, instructions, communications, constant (meta) cognitive navigation should be developed to facilitate significant learning and cognitive processes (Martin et al., 2021; Ofelia San Pedro & Baker, 2021). Indeed, certain systems and models developed by artificial intelligence and adaptive learning communities might not be successful in interpreting the dynamic external and internal learning processes with cyclical recommendation, constantly iterative adaptation and recursive feedback loops that promote cognitive flexibility.

This generic design ecosystem is expected to improve system's versality and flexibility by intelligent adaptive prediction, recommendation, sequences, adjustments, scaffolding, and dynamic feedback loops that can be suitable for addressing unique requirements of teaching, learning and evaluation. These intelligent technologies (e.g., machine learning, natural language processing, artificial neural networks, and Bayesian networks) are supposed to be able to formulate adaptive activities and metacognitive tools that meet varying needs, learners' interests and personal traits (e.g., prior knowledge, learning goals, preferences). The system' agility, user's capabilities, learning adaptability (e.g., learners' levels of mastery, problem-solving competency, metacognitive abilities), and learning impacts (e.g., levels of trust, technology acceptance and user satisfaction) should be coordinated and optimized across the different contexts of educational management, diverse domains and learning subjects, types of pedagogical tutors or agents (Jones et al., 2018).

By combining adaptive components and elements, field experts employ adaptive models and techniques to design, predict and determine types of adaptive learning support that should improve the capacities of adaptivity and user experience (Plass & Pawar, 2020; Dutchak et al., 2021; Darvishi et al., 2022; Giannakos & Cukurova, 2023). Adaptive learning analytics and evaluation systems or applications monitor and track users' interactive behaviors, learning trajectories, memory curve, emotional status, and internal cognitive processes. The measurement of these datasets and types requires to be evaluated by experts (e.g., educators, learning analysts, didactic or pedagogy engineers) in the regard of the feasibility and sustainability of adaptive programs. For instance, determining which sorts of learning evidences (e.g., number of successes; misconceptions or errors; efficiency in solving problems of exercises or practical work; efforts or number of times in attempts, time spent; memory curves; (meta) cognitive strategies) that can characterize users' motivation, learning progresses, learning gains and learning difficulties. All of these factors can be analyzed and evaluated by applications or systems modeling approaches with machine learning techniques, and human manual methods. Moreover, advanced intelligent and adaptive deep learning techniques can obtain physiological and psychological data (e.g., postures, emotional responses, eye movement, social interactive behavior, meta cognition, meta emotion, motivation, and consciousness) throughout multi-modal channels and models' optimization (S.-M. Park & Kim, 2022). These learning results and knowledge circulations serve purposes in improving types of learning analytics (e.g., descriptive analytics, diagnostics, predictive modeling, inferential, prescriptive, and (meta) cognitive analytics), evaluation methods (automated, semi-automated methods, formative and summative feedbacks), and optimization of multimodal learning and (meta)cognitive intervention (e.g., hints, indices, remedies, feedbacks, suggestions and recommendations) (Kautzmann & Jaques, 2019b; Munshi et al., 2023). These knowledge and experiences can be useful for educational sectors and practitioners to readjust pedagogical plans, curriculum sequences, to optimize agent systems and adaptive learning activities (F. Weber et al., 2021).

ALE exhibits enhanced capacities by effective and advanced model construction, intelligent adaptive features and targeted functions to provide adaptive scaffolding, and ensure learning adaptability (Martin et al., 2021; Stan et al., 2022). Certain range of intelligent tutoring systems, adaptive instruction, adaptive recommendation systems, may lead to different levels of learning efficiency and satisfaction. The incorporation of open learner models has been proved in enabling learners to increase self-efficacy behaviors and improve learning outcomes by observing learning progress and levels of knowledge they have acquired (Jones & Castellano, 2018). Open flexible learning models incorporate optimized constant resources to facilitate learners' adaptive regulative strategies and co-regulative skills. Metacognitive auxiliary models and intervention mechanisms assist users to view overall performance for the reflection of self-efficacy strategies, to provide personalized feedbacks for the construction of metacognitive scaffolding (Kautzmann & Jaques, 2019; Matsuda et al., 2020; H.-S. Wang et al., 2021; Carlon & Cross, 2022a; Guo, 2022). These methods, which emphasized embodied cognition and meta level scaffolding activities to support for reinforcing deeper learning approaches, professional development and further integration of adaptive expertise, have been recognized as significant research trend in adaptive learning communities. In parallel, learners can collaborate with systems, pedagogical innovation practitioners or peers to develop human-centered, responsible, and sustainable intelligent personalized adaptive learning environments to ensure higher-order knowledge mastery and user experience.

7.3.3 The Impacts of Adaptive Learning Ecosystem Framework

ALE enables the consistent influences in improving system's versality, flexibility, compatibility, adaptivity, learning adaptability when rich resources, didactic frameworks, adaptive models and personalized learning techniques are appropriately incorporated by institutions and transdisciplinary experts (Y. Chen et al., 2019; Plass & Pawar, 2020; F. Weber et al., 2021; Schlimbach et al., 2022; Stanney et al., 2022). Adaptive learning beneficiaries guided by ALE framework should exhibit improved capacities of expertise integration, considering active cognitive processes construction with prior knowledge and experiences in choices related to the strategies of optimization of ongoing resources, digital platforms, intelligent evaluation, adaptive programs, effective communication mechanisms for users. Furthermore, the ALE framework highlights the applicability across varying educational projects, contexts, domains, emphasizing its agility and adaptivity for addressing the specific objectives and diverse needs of different settings. The integrative adaptive frameworks and mechanisms encapsulate the transformative potential of the ecosystem on guiding adaptive learning experts towards evidence-based policies-making, effective implementation, evaluation, and the creation of inclusive, hybrid flexible, adaptive learning environments in the contexts. This proposed generic ecosystem framework contributes common reference of strategies and policies of development and adaptive regulations to the field, offer theoretical foundations and reference guidelines for further research, and reinforce the framework' significance in the dynamic landscape of adaptive learning processes.

ALE highlights the importance in the employment and incorporation of adaptive LM, intelligent AI, and user-centric LA, as mediating tools for enhancing adaptive learning, and how educational practitioners, and learning beneficiaries interact with newly pedagogical approaches and generative adaptive technical models. The knowledge, evidence and experience collected in the studies should contribute to formulate adaptive design principles and evaluation strategies. Future research can apply these propositions to improve intelligent, adaptive, deeper learning approaches, and also incorporated constructed models to test and adapt in the newly designed environment.

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RÉSUMÉ SUBSTANTIEL

Reflection of the construction and impacts of adaptive learning ecosystem

Dans le cadre de cette thèse en sciences de l'éducation et de la formation, nous nous penchons sur l'étude d'un écosystème d'apprentissage adaptatif et personnalisé. Nous essaierons de tracer les grandes lignes du sujet traité dans cette recherche afin de proposer au lecteur une vue globale. La particularité de ce parcours de recherche est qu'il se situe au carrefour des Sciences, de l'Informatique et des Sciences de l'Éducation et de la Formation ; il permet d'étudier et de développer des pratiques transdisciplinaires visant à répondre aussi bien à des besoins industriels qu'à des besoins sociaux.

L'étude des Environnements d'Apprentissage Adaptatifs (EAA) a connu des avancées spectaculaires ces dernières décennies. La mesure de leur impact revêt une importance primordiale à différents niveaux (politique, éducatif, culturel, éthique, économique, commerciaux, …). Le potentiel positif des applications éducatives assistées par l'Intelligence Artificielle (IA) est souvent pointé, à savoir que l'utilisation des EAA serait efficace pour l'augmentation de la cognition et de l'apprentissage humains, tel est la présupposé discours apologétiques des promoteurs de ces nouvelles technologies. Plusieurs questions restent en suspens en ce qui concerne le potentiel de l'IA et de ces nouvelles technologies, c'est cette préoccupation qui nous a conduit vers ce domaine de recherche des Ingénieries des Environnements Informatiques pour l'Apprentissage Humain (IEIAH) et de développement spécifique qui alimentent un nouveau paradigme. L'objectif de cette recherche est d'étudier empiriquement les environnements d'apprentissage éducatifs innovants pour s'adapter aux besoins différenciés des apprenants, et augmenter l'apprentissage pour atteindre des objectifs pédagogiques visés.

Notre recherche se situe dans l'entrée 1 « La genèse des savoirs dans les institutions didactiques » de notre laboratoire "Éducation - Formation - Travail - Savoir"[8] (EFTS). Ce travail de recherche a été réalisé au sein du groupe de recherche pluridisciplinaire[9] Serious Game Research Lab (SGRL) qui possède une expertise dans la conception et l'évaluation des environnements numériques pour

[8] Laboratoire EFTS, "Education - Formation - Travail - Savoir". UMR EFTS MA 122 qui est structuré en trois entrées thématiques.
[9] Groupe de Recherche Pluridisciplinaire INU Champollion : *https://www.univ-jfc.fr/grp/serious-game-research-lab-sgrl*

l'apprentissage (Galaup, 2020). Le travail scientifique de cette recherche a été effectué dans le cadre du projet Et-Lios[10] « Enseignements Technologiques de niveau LIcence Ouverts pour une industrie du futur compétitive et Soutenable » qui est porté par un consortium issu du Groupement d'Intérêt Scientifique (GIS) S.mart (ex réseau AIP-PRIMECA) répondant à l'appel à projet PIA Hybridation des formations d'enseignement supérieur. Dans ce projet, le SGRL a piloté le sous projet intitulé « Mesure de l'impact » qui consiste à fournir une évaluation ; un retour d'expérience de la valeur ajoutée autour du projet, de ses plateformes numériques et des modules pédagogiques hybridés. Nous avons donc eu en charge, la mesure de l'impact afin de pouvoir dégager des enseignements sur les axes de mobilisation de ces formations digitales et de fournir des indicateurs sur la qualité des formations scientifiques et technologiques qui sont proposées dans la communauté S.mart. L'originalité de ce travail de recherche repose sur une méthodologie expérimentale rigoureuse qui s'appuie sur une conception d'environnements d'apprentissage adaptatifs (EAA) et sur leurs évaluations in situ (Galaup, 2020). Les résultats produits par ce manuscrit nous ont permis d'étudier, selon une double posture, les effets de la mise en œuvre d'un environnement d'apprentissage adaptatif (EAA) et certains aspects de leur conception. Enfin, la conclusion de cette recherche synthétise les résultats issus de cette expérimentation, propose un écosystème d'apprentissage adaptatif et des suggestions pour la poursuite de la recherche.

L'architecture de cette thèse pourrait se présenter ainsi :

- Revue de littérature sur les environnements d'apprentissage adaptatifs, les théories d'apprentissage, les modèles adaptatifs et proposition d'un cadre théorique.
- Conception et développement d'un environnement d'apprentissage adaptatif ainsi que des scenarios pédagogiques associés. Conception collaborative entre les enseignants, les chercheurs et l'ingénieur d'étude chargée du développement informatique.
- Conception du protocole d'expérimentation (construction des indicateurs, définition des données à collecter et des analyses à effectuer, définition du plan de gestion des données).
- Mise en place des expérimentations, collecte et stockage des données.
- Analyse des données en collaboration avec les membres du projet.
- Conclusion et perspectives de recherche.

1.1 Introduction

[10] PIA 3 **Et-Lios** (https://et-lios.s-mart.fr) Enseignements Technologiques de niveau LIcence Ouverts pour une induStrie du futur compétitive et durable. Projet d'hybridation des formations de l'enseignement supérieur 2020

Le présent paragraphe nous permettra d'examiner les EAA, leur évolution, et les problématiques liées à leurs utilisations et à leurs conceptions. Les EAA sont progressivement passés d'une approche pédagogique techno-centrée, qui se concentre principalement sur la transmission des connaissances d'un expert ou d'un système intelligent artificiel à l'apprenant, à une approche centrée sur l'humain, dans laquelle les connaissances sont construites par éventail d'acteurs apprenants qui participent activement à l'expérience d'apprentissage et sont engagés dans un travail collaboratif avec l'EAA, les experts et leurs pairs.

Nous nous attendons à ce que les environnements d'apprentissage adaptatifs offrent de meilleures solutions d'apprentissage personnalisées centrées sur l'humain et permettent un apprentissage plus autonome, autodirigé, autorégulé et auto-efficace. L'apprentissage auto-adaptatif peut être défini de manière générale comme l'adaptation de l'être humain dans un monde complexe. Des systèmes d'apprentissages hybrides ou adaptatifs, permettent d'obtenir des ressources d'apprentissage, de découvrir ses propres motivations et préférences, d'interagir avec les contenus adaptatifs, de collaborer avec les autres et d'obtenir un soutien pendant le processus d'apprentissage. D'autres points positifs existent comme l'acquisition de connaissances et de compétences requises, la construction d'un sens personnel et le développement de soi à partir de son expérience d'apprentissage personnelle.

Cependant, la construction d'un écosystème d'apprentissage adaptatif et personnalisé soulève plusieurs problèmes. Dans la plupart des systèmes, les sources et les types d'adaptation sont souvent pris en compte de manière insuffisante. En d'autres termes, l'étude et la mise en œuvre des questions d'adaptabilité ne sont pas suffisantes. La plupart des environnements d'apprentissages adaptatifs ne considèrent qu'un seul type d'adaptation en raison du manque d'intégration de l'innovation des connaissances interdisciplinaires, de la gestion des ressources humaines, de l'avancement de la technologie, de la systématisation de multiples systèmes et de services dans les programmes d'apprentissages adaptatifs. La collecte de données d'apprentissage souffre de problèmes d'insuffisance, de diversité, d'utilité, de validité, de valeur ce qui rend l'analyse de l'apprentissage moins facile pour générer une évaluation efficace des solutions pour fournir un apprentissage adaptatif réellement personnalisé (Brusilovsky et *al.,* 2020). En outre, un grand volume de ressources peut submerger les apprenants pendant le processus d'apprentissage s'ils ne savent pas comment, quand, où et quoi apprendre mieux ou efficacement. Cela peut conduire à une charge cognitive et fait que les apprenants transfèrent moins efficacement leurs connaissances en compétences. Les environnements d'apprentissage en ligne adaptatifs traditionnels ont tendance à fournir des règles d'adaptation fixes et préétablies dans le même ordre à des groupes d'utilisateurs particuliers, ce qui peut poser un problème de personnalisation et entraîner une expérience et des performances médiocres. L'adaptation est souvent mise en avant comme un moyen de personnaliser l'apprentissage, de personnaliser les services, ou d'adapter un système aux besoins de l'utilisateur (Yuan et *al.,* 2018). Certains systèmes d'apprentissage tels que le Système de Tutorat Intelligent (STI), le système pédagogique adaptatif, le système d'apprentissage adaptatif émotionnel, le système d'apprentissage adaptatif intelligent, le système d'accompagnement adaptatif, le système d'apprentissage adaptatif personnalisé, intègrent différents modèles théoriques pour fournir des services adaptatifs et recommander du matériel pédagogique personnalisé pertinent. Un système d'apprentissage approfondi adaptatif peut, par exemple, mettre l'accent sur des matériels appropriés et opportuns, recommander des contenus pour un apprenant donné, effectuer une évaluation adaptative, construire des séquences d'apprentissage personnalisées, ou naviguer dans les parcours d'apprentissage.

Dans ce manuscrit, nous présentons, d'une part, des recherches concernant l'adaptation individuelle dans l'écosystème d'apprentissage adaptatif dans lequel l'apprentissage peut être personnalisé et séquencé de manière appropriée pour répondre aux besoins des apprenants individuels. D'autre part, nous adoptons une approche transdisciplinaire qui puise dans les domaines de l'éducation, de l'informatique, des sujets STEAM[11], la psychologie, la science cognitive, des données. Les questions de recherche spécifiées de cette thèse trouvent leurs réponses en combinant les concepts théoriques et les preuves empiriques de disciplines majeures.

Dans le domaine des sciences de l'éducation et de la formation, plusieurs modèles conceptuels s'inspirent des théories psychologiques telles que la psychologie humaniste, béhavioriste, constructiviste, la psychologie du développement, la psychologie de la Gestalt[12], les théories de l'apprentissage social. D'autres théories entrent en jeu, comme, les théories cognitives telles que la charge cognitive, la flexibilité cognitive, la sémiotique cognitive et d'autres théories telles que le connexionnisme, le connectivisme, l'apprentissage par le jeu, les théories des styles d'apprentissage. D'un point de vue épistémologique, lors de la conception et de la mise en œuvre de systèmes d'apprentissage, il est crucial d'identifier pourquoi, quand, où, comment et ce que les utilisateurs préfèrent apprendre et peuvent apprendre correctement. La compréhension des différents traits personnels a été la question clé dans le développement de la personnalisation et de

[11] STEAM est un acronyme anglais provenant des mots Science, Technologie, Ingénierie, Art et Mathématiques (Science, Technology, Engineering, Arts, Mathematics). https://fr.wikipedia.org/wiki/Steam
[12] https://www.usabilis.com/definition-theorie-de-gestalt/

l'adaptation afin de répondre aux exigences de l'apprenant. Parmi ces variables, la maîtrise des connaissances et l'expérience d'apprentissage sont reconnues comme des facteurs majeurs de l'apprentissage.

Dans le domaine de l'informatique, la recherche d'un système d'apprentissage personnalisé et adaptatif reste une question cruciale pour les chercheurs. Le développement de méthodes, techniques et outils adaptatifs représente une préoccupation importante dans l'écosystème de l'apprentissage adaptatif. Ces techniques précisent la manière dont le contenu d'apprentissage est présenté et séquencé pour répondre aux besoins des apprenants. Un point central de cette recherche concerne le développement de modèles et de cadres adaptatifs qui visent à faciliter la mise en œuvre de systèmes adaptatifs ; les cadres intègrent les principaux composants qui sont nécessaires ou importants pour permettre l'adaptation, tels que le modèle du domaine, le modèle pédagogique, le modèle de l'apprenant, le modèle de l'interface utilisateur, le modèle de gestion et le modèle d'adaptation. Certains modèles supplémentaires tels que le modèle auxiliaire métacognitif, le modèle analytique d'apprentissage adaptatif, le modèle d'évaluation adaptatif sont également proposés pour la réflexion sur la construction d'une expérience d'apprentissage plus profonde d'auto-efficacité.

Le chapitre suivant présente la motivation de ce travail et le contexte pertinent. Il expose également les problèmes de recherche qui sont identifiés. Il précise ensuite les objectifs, les questions et la méthodologie de la recherche, et met en évidence la contribution de cette recherche.

1.2 Revue de la littérature

Dans cette section nous allons recenser les EAA et dresser un état des lieux des différentes réflexions à leur sujet en mettant l’accent sur leurs apports et leurs limites. L’objectif n’est pas de prendre en compte la totalité des EAA existant mais de revenir sur les théories pertinentes pour notre recherche afin de particulariser le discours général et d’identifier quelques pistes qui contribueront à notre problématique.

L’apport de contenus et de ressources d'apprentissage qui tiennent compte des caractéristiques individuelles telles que le niveau de connaissances, l'expérience antérieure, les capacités cognitives, les préférences d'apprentissage et les différences culturelles est appelée apprentissage personnalisé ou enseignement adaptatif. Mais, ces considérations ne permettent pas nécessairement un apprentissage adaptatif dynamique qui tienne compte des variables de la cognition, des émotions et du comportement (Vandewaetere, Desmet & Clarebout, 2011). L'adaptation et l’apport de matériel pédagogique jouent un rôle crucial dans l'amélioration de l'apprentissage personnalisé. L'enseignement adaptatif, fait référence à une approche et/ou une intervention éducative. Selon Park & Lee (2013), il intègre des procédures, des stratégies alternatives pour l'enseignement, l'utilisation des ressources et il a la flexibilité intégrée. Ainsi, il permet aux individus ou aux différents groupes d'étudiants de prendre différentes voies et du temps pour apprendre, acquérir ou développer des connaissances et compétences pour accomplir les tâches ou atteindre des objectifs (Park & Lee, 2013). Cette approche et/ou intervention éducative est généralement basée sur une approche de l'enseignement qui fournit une instruction et un tutorat adaptatifs s’appuyant sur les informations du profil descriptif de l'apprenant telles que le niveau de connaissances antérieures, l'expérience, les antécédents, ... Ces données peuvent être évaluées par le pré-test ou le post-test qui conduisent à la détermination de l'affectation appropriée des unités d'enseignement et à faciliter la différenciation de l'apprentissage pour répondre aux besoins des individus (Shute & Towle, 2018). L'apprenant peut être tenu d'atteindre un niveau prédéfini de maîtrise de l'unité apprise avant de passer aux niveaux appropriés suivants. Cependant, ce type d'adaptation souffre de la limitation du temps disponible, des ressources et de la capacité à évaluer les différentes réalisations et l'efficacité de la mise en œuvre (Brusilovsky et al., 2022, Wilson & Scott, 2017).

Avec l'avènement des technologies émergentes (Intelligence Artificielle), de nombreux systèmes d'apprentissage adaptatifs ont été développés pour proposer un apprentissage personnalisé dynamique qui aide les apprenants à accéder à un système éducatif interactif et intelligent basé sur le Web. Selon plusieurs auteurs, ce dernier fournit un tutorat intelligent, des technologies adaptatives telles que ELM-ART, des manuels intelligents, des cours, des exercices, pour interagir et collaborer avec les autres apprenants, et obtenir des recommandations, une navigation et un retour d'information instantanée (Weber & Brusilovsky, 2016 ; Brusilovsky, Sosnovsky & Thaker, 2021 ; Brusilovsky et al., 2022). Ces systèmes améliorent la personnalisation dans le cadre de la salle de classe traditionnelle qui offre généralement les mêmes séquences pour les apprenants indépendamment de leurs caractéristiques variables personnelles. Ces systèmes d'apprentissage fournissent des présentations sur mesure de supports d'apprentissage, des séquences et offrant des possibilités d'apprentissages adaptatifs personnalisés à tout moment et partout pour répondre aux exigences individuelles. Ces systèmes d'apprentissage adaptatifs qui incorporent certains caractères d'adaptativité et d'adaptabilité par le biais du contrôle de l'utilisateur ou du système avec des méthodes, des techniques et des outils adaptatifs, ont été développés et sont inspirés par le système de tutorat intelligent (ITS) et l'hypermédia adaptatif ou d'autres systèmes d'apprentissage adaptatifs émotionnels (Çebi, Araújo & Brusilovsky, 2022 ; Wilson & Scott, 2017).

L'informatique “en nuage[13]“, avec ses avantages tels que l'autonomie, la rentabilité, la flexibilité et la fiabilité de l'infrastructure, permet la création d'un écosystème d'apprentissage en ligne. Ainsi, l'intégration de l'informatique en nuage dans les services d'apprentissage en ligne en classe joue un rôle important dans l'avenir de l'éducation adaptative. L'apprentissage adaptatif, les campus intelligents, l'évaluation des enseignants, les robots tuteurs intelligents et les classes virtuelles ne sont que quelques-unes des applications de l'IA éducative (Ashraf Alam, 2023). D'un point de vue technique, les EAA sont des systèmes d'enseignement et de tutorat intelligents développés à l'aide de techniques d'intelligence artificielle telles que les arbres de décision, la logique floue, les réseaux bayésiens, les réseaux neuronaux. Comme mentionné précédemment, nombreux sont les auteurs qui identifient des facteurs importants dans l’apprentissage comme le style d'apprentissage, le niveau cognitif, la maîtrise des connaissances et l'expérience d'apprentissage (Clarebout, 2011 ; Alshammari et al., 2014 ; Essalmi et al., 2015).

Nous recensons et décrivons ici quelques systèmes offrant de l'adaptation par le style d'apprentissage. Les systèmes éducatifs adaptatifs basés sur les styles d'apprentissage (AEHS-LS) visent à adapter les supports éducatifs individuellement aux apprenants. Le système INSPIRE est basé sur le modèle de style d'apprentissage de Honey et Mumford (AEHS-H&M). Le système AMDPC s’appuie sur le modèle de style cognitif de Witkin et le modèle de style d'apprentissage de Felder-Silverman. Quant à eux, les systèmes CS383, MASPLANG, LSAS, TANGOW reposent sur le modèle de style d'apprentissage de Felder et Silverman. De même, le système MOT est basé sur le modèle de style d'apprentissage de Kolb et le système PALS2 est basé sur le Learning Styles Profiler de Jackson. L’AEHS-LS s’appuie sur le modèle de style d'apprentissage VARK ; le système iWeaver prend source sur le modèle de style d'apprentissage de Dunn et Dunn ont été évalués, et ont indiqué une meilleure performance significative (Mustafa & Sharif, 2011 ; Drissi & Amirat, 2016 ; Tsortanidou, Karagiannidis, Koumpis, 2017). Par exemple, INSPIRE représente un système d'instruction intelligent basé sur le style d’apprentissage, le niveau de connaissances et les progrès des apprenants qui personnalise l'instruction, génère dynamiquement des leçons qui conduisent progressivement à l'accomplissement des objectifs d'apprentissage sélectionnés par l'apprenant. Par exemple, CS383 est une interface hypermédia adaptative et un didacticiel qui ont

[13] Traduction littérale de « *Cloud* »

été développés pour personnaliser la présentation du matériel de cours en fonction du style d'apprentissage de l'utilisateur. Le système "iWeaver" est un environnement d'apprentissage adaptatif basé sur le Web qui met en œuvre différentes formes d'adaptation, fournit un cours d'introduction à la programmation informatique en accord avec les styles d'apprentissage des utilisateurs (Tsortanidou, Karagiannidis & Koumpis, 2017). Un exemple récent de réussite est le système de tutorat de programmation (ProTuS), qui fournit un contenu intelligent et interactif, des options de personnalisation, des fonctions adaptatives et des analyses d'apprentissage pour soutenir les utilisateurs engagés dans l'apprentissage de compétences cognitives complexes (Vesin, Mangaroska et Giannakos, 2018).

La plupart des systèmes adaptatifs prennent des décisions en utilisant une seule source d'informations de personnalisation, certains systèmes comme le système TSAL utilisent deux sources d'informations de personnalisation : le comportement d'apprentissage et le style d'apprentissage. Ce système interactif prend en compte les interactions de l'apprenant avec le système, utilise le comportement d'apprentissage, qui comprend la réalisation ou les résultats de l'apprentissage, les besoins d'apprentissage et le temps pris pour effectuer les tâches (degré d'engagement et de concentration) pour attribuer le style d'apprentissage et déterminer le style de présentation séquentielle et les niveaux de difficulté des matériaux ultérieurs. Les systèmes de tutorat intelligent ont fourni un apprentissage adaptatif basé sur la négociation avec la fonctionnalité de soutien aux apprenants ayant des besoins d'apprentissage, comme le tuteur cognitif (Chou et al., 2018 ; Tseng et al., 2008).

Nous pouvons, dès à présent, établir quelques remarques concernant ces différents systèmes offrant de l'adaptation par le style d'apprentissage. Il n'est pas toujours clair de savoir quels sont les indicateurs, variables, méthodes et défis qui sont les priorités de la mise en œuvre et, comment les intégrer à l'adaptation dans les différents modèles dans l'environnement d'apprentissage adaptatif en général. Nous réfléchissons plus particulièrement, s'il est possible d'intégrer autant de sources d'adaptation avec différentes méthodes, techniques et outils. Nous nous questionnons pour savoir comment les acteurs de l'apprentissage peuvent évaluer l'efficacité de ces initiatives d'adaptation avant leur mise en œuvre empirique. La recherche actuelle pointe une insuffisance de coopération transdisciplinaire de différentes parties prenantes de l'apprentissage pour fournir plus d'adaptation. Pour de nombreux auteurs si la cible de l'adaptation est déterminée par la performance, le comportement, l'affection et les aptitudes des étudiants rares sont les évaluations empiriques de haute qualité (Standen et al., 2021 ; Truong 2016 ; Özyurt et Özyurt, 2015 ; Tlili et al., 2016).

Aujourd’hui, les établissements d'enseignement supérieur sont de plus en plus intéressés par l'utilisation de l'apprentissage adaptatif basé sur les données comme solution innovante pour évaluer l'enseignement. L'adoption réelle des attitudes et des opinions des acteurs de l'éducation dans la mise en œuvre de l'apprentissage adaptatif dans les cours reste insuffisante. Ceci conduit à la conception de systèmes d'apprentissage adaptatifs se concentrant sur l'évaluation empirique de la façon d'améliorer le processus d'apprentissage basé sur l'adaptation sur les styles d'apprentissage, sur les préférences d'apprentissage, sur la difficulté d'apprentissage, et sur les exigences d'apprentissage. Ce changement diffère de la façon “antérieure” qui était fondée sur l'amélioration de la performance d'apprentissage basée sur l'expérience antérieure et les résultats actuels, sur l'évaluation adaptative des logiques et de la durabilité, sur la conception du soutien dans le développement de différents types de connaissances et sur l'amélioration de l'aptitude ou de la compétence.

L'adaptation basée sur le style d'apprentissage, le niveau de connaissance, l'efficacité de l'apprentissage, les stratégies cognitives psychologiques, métacognitives, dans l'environnement d'apprentissage a été considérée comme un domaine de recherche important. Les raisons sont la complexité inhérente de l'adaptation, le grand nombre de modèles et de dimensions du style d'apprentissage, les mesures de la cognition, de la psychologie, de l'échafaudage adaptatif, du feedback, des méthodes d'intervention, des techniques avancées, des outils et des nombreuses variables qui doivent être analysées, sélectionnées lors de l'évaluation de la faisabilité, des impacts et de la durabilité de l'adaptation.

Bien qu'il y ait eu de plus en plus de tentatives pour construire des mécanismes d'apprentissage adaptatifs pour améliorer l'apprentissage, Brusilovsky (2022) soutient qu'il y a un manque d'évaluation expérimentale suffisante et soigneusement conçue de l'efficacité, et propose l'adaptation basée sur le modèle d'analyse de l'apprentissage adaptatif pourrait être plus important que de proposer de nouvelles techniques d'adaptation avec des avantages discutables (Brusilovsky et al., 2022; Sarıyalçınkaya et al., 2021). Un autre défi est l'insuffisance de l'évaluation expérimentale de l'utilité et des impacts des variables qui sont habituellement considérées pour déterminer le mode d'adaptation. Certains facteurs cruciaux tels que les perspectives didactiques, épidémiques et cognitives devraient être pris en compte lors de l'évaluation de l'adaptabilité et de l'adaptabilité des systèmes d'apprentissage (Mavroudi, Giannakos & Krogstie, 2018). Les résultats des études concernant l'adaptation basée sur les modèles de style d'apprentissage ne sont pas concluants, cela reste la limitation dans la confiance de la généralisation de l'effet d'apprentissage car il fait face aux défis des applications à petite échelle et à court terme dans de petits échantillons d'apprenants (Truong, 2016 ; Özyurt & Özyurt 2015 ; Alshammari et al., 2015). En ce qui concerne l'évaluation des systèmes d'apprentissage adaptatifs, les méthodologies d'évaluation telles que l'évaluation expérimentale de l'interaction homme-machine (IHM) ou de la collaboration homme-ordinateur (CEH) ont été considérées comme une priorité des méthodes les plus adaptatives (Mulwa et al., 2012). Le cas a été fait que l'évaluation par l'expérimentation ou des tests avec des apprenants pratiques autorégulés est nécessaire dans la réflexion de l'amélioration des systèmes adaptatifs, car il génère la preuve de l'utilisabilité, la faisabilité, l'utilité et l'acceptabilité (Muller et al., 2017).

A la suite de Brusilovsky (2022), nous avons choisi une évaluation expérimentale soigneusement conçue pour évaluer la faisabilité des différentes formes d'adaptation, en particulier par des essais pilotes menées pour répondre aux questions de recherche, aux objectifs et hypothèses spécifiques. Elle joue un rôle dans la détermination des avantages, l'efficacité et l'utilisabilité d'un système par l'observation, l'analyse et la réflexion dans une approche contrôlée dans des situations réalistes. En outre, la pertinence de cette approche d'évaluation peut être justifiée à partir de la preuve du public cible, car la principale source de données est généralement générée à partir de l'interaction utilisateur-système (Mulwa et al., 2012).

1.3 Cadre de la recherche

La recherche présentée dans cette thèse s’inscrit à la croisée de plusieurs cadres théoriques. Cette section s’organise en quatre paragraphes qui présentent les principaux modèles et cadres adaptatifs visant à faciliter la mise en œuvre de systèmes adaptatifs. Dans ce résumé nous nous limiterons à la présentation du modèle du domaine, du modèle d'apprenant, du modèle pédagogique, et du moteur d'adaptation. L'analyse des modèles s’appuie sur i) les indicateurs et critères d'adaptation ; ii) les méthodes et techniques de modélisation ; iii) les défis et opportunités de la modélisation.

1.3.1 Modèle du domaine

Selon McCoy, (2018) le domaine représente l'espace d'information qui correspond à la conscience collective implicite et explicite, déclarative et procédurale, des experts en ingénierie des connaissances. La connaissance du domaine est un concept d'ingénierie des connaissances et peut être définie sous de nombreuses formes différentes en fonction des situations d'apprentissage et des exigences de modélisation. Elle peut être utilisée dans la découverte de processus guidée par les données qui est une discipline clé de l'exploration de processus qui permet différentes méthodes et techniques pour apprendre un modèle de processus à partir de données d'événements pour améliorer les processus opérationnels (Schuster et *al.,* 2022). Avec cette représentation de la hiérarchie des objectifs de connaissance, du niveau de connaissance de l'apprenant et du concept, du graphe de connaissance, de la structure de connaissance, des ressources de connaissance du contenu ; de nombreuses opérations intelligentes telles que l'extraction automatique de concepts pourraient être effectuées. Cela inclut la modélisation de l'étudiant, l'aide à la navigation adaptative et la recommandation de contenu. Ce modèle a été présenté comme une nouvelle approche qui combine des solutions d'ingénierie des connaissances et des connaissances entièrement automatiques pour recommander des activités d'apprentissage adaptatives, intelligentes, interactives et utiles, des ressources, des manuels électroniques ou intelligents pour soutenir des scénarios d'apprentissage puissants qui ont indiqué les plusieurs avantages de l'évidence du comportement des apprenants. La modélisation avancée du domaine et la modélisation améliorée de l'étudiant permettent des approches de personnalisation plus puissantes pour les plateformes de manuels numériques afin de permettre des recommandations adaptatives basées sur le comportement en temps réel des étudiants pour un apprentissage avancé dans les manuels et la remédiation. L'évaluation, y compris les résultats de l'évaluation formative et de l'évaluation sommative, joue un rôle crucial dans l'apprentissage adaptatif, car elle fournit au public cible un retour d'information basé sur le critère d'évaluation de l'efficacité de sa performance. L'expérience menée indique que les résultats de l'incorporation de l'état actuel des connaissances de l'étudiant sur le concept de domaine associé à l'activité pour recommander des sections de rattrapage personnel améliorent considérablement la qualité de la recommandation par rapport aux recommandations traditionnelles basées sur le contenu (Thaker et *al.,* 2020 ; Brusilovsky, Sosnovsky & Thaker, 2022). Les avancées dans les outils d'aide à la modélisation et de génération de modèles, y compris les outils d'acquisition de modèles de domaine, ne garantissent pas des modèles parfaits, car la création et la maintenance des modèles de domaine est un goulot d'étranglement bien reconnu et reste un défi dans l'utilisation de la planification automatisée. Le développement du modèle de planification de l'ingénierie des connaissances comme un processus itératif dans la génération de plans efficaces, alimenté par un modèle précis d'une application dans le moteur de planification est essentiel dans l'innovation des solutions d'ingénierie des connaissances (Jilani et *al.,* 2014 ; Gregory & Lindsay, 2016 ; Lindsay & Petrick, 2022).

1.3.2 Modèle d'apprenant

Ce modèle d'apprenant représente l'adaptation basée sur les exigences de l'apprentissage et des apprenants, y compris les styles d'apprentissage, les traits personnels, la structure cognitive, traits, tandis que les techniques de détection informatisées étaient couramment appliquées pour identifier les traits personnels d'un apprenant dans un environnement d'apprentissage adaptatif (Normadhi et *al.,* 2019). L'objectif de la modélisation des modèles d'apprenants est de conduire la personnalisation en fonction des variables d'apprentissage considérées comme importantes pour le processus d'apprentissage, telles que les aspects de la cognition, de l'affection et des comportements. Le modèle traditionnel de l'apprenant est resté caché et son rôle est de permettre au système de personnaliser l'interaction. Le modèle d'apprentissage ouvert (OLM) encourage les apprenants à participer activement à la réflexion et à l'élaboration de leur propre apprentissage, il est maintenu comme le modèle d'interface approprié qui permet la visualisation des connaissances et des progrès pour les utilisateurs, y compris les apprenants, les pairs, les enseignants, les administrateurs. Le modèle de l'apprenant sous des formes attrayantes, utiles et compréhensibles fournit des méthodes, des techniques et des outils efficaces pour promouvoir la réflexion, la planification, la navigation et d'autres activités métacognitives qui sont importantes dans le développement de mécanismes adaptatifs personnalisés et favorisent un apprentissage plus approfondi à partir d'un processus significatif (Hooshyar et *al.,* 2020 ; Susan Bull, 2020 ; Guerra-Hollstein et *al.,* 2017).

Bien que plusieurs études aient suggéré que la technologie pourrait influencer les stratégies cognitives, la métacognitive, y compris la conscience de soi de l'apprenant, l'autorégulation et la capacité de surveillance de manière positive, les effets de l'apprentissage adaptatif restent des preuves et une évaluation insuffisante. Pendant ce temps, le modèle d'apprentissage social ouvert (OSLM) encourage la modélisation avec l'extension des fonctionnalités de comparaison sociale qui pourraient améliorer la motivation d'apprentissage, la réussite et leurs capacités de suivi des connaissances absolues et relatives, y compris la capacité d'auto-réflexion et d'auto-évaluation (Susan Bull, 2020 ; Somyürek, Brusilovsky & Guerra, 2020). L'application de l'apprentissage par le jeu dans un environnement d'apprentissage adaptatif devrait améliorer le processus d'apprentissage social car il offre des fonctionnalités de comparaison sociale pour accéder aux données en cours (Leonardou, Rigou & Garofalakis, 2019).

Bien que la co-création pour l'innovation sociale dans l'écosystème de l'apprentissage soit devenue la tendance des établissements d'enseignement supérieur à s'impliquer dans les pratiques d'innovation sociale, ils ont étendu la contribution de l'enseignement et de la recherche à la résolution de problèmes socio-économiques. Les méthodes, techniques, outils et activités d'apprentissage collaboratif adaptatif des plateformes d'innovation ouverte pour des actions collectives aident les acteurs à s'engager avec la société et à renforcer la collaboration. Elles doivent être développées en soutenant le problème, le projet, la compétence basée l'apprentissage et la diffusion des connaissances à l'aide d'une approche transdisciplinaire ; respectant un équilibre entre les solutions centrées sur la connaissance, l'humain, la collaboration et la transformation relationnelle qui sont les principaux catalyseurs pouvant promouvoir l'innovation sociale (Kumari et *al.,* 2019). Les revues actuelles indiquent le manque d'études dans l'innovation de l'ouverture de l'apprentissage social et de la collaboration pour faciliter un apprentissage personnalisé, adaptatif et approfondi qualifié. Leurs rôles et leurs relations dans le soutien au développement et à l'intégration de l'expertise devraient être explorés plus avant.

1.3.3 Modèle pédagogique

Plusieurs études révèlent que les systèmes éducatifs adaptatifs (AES) tels que les systèmes pédagogiques adaptatifs (AIS), les systèmes de tutorat intelligents (ITS), les systèmes hypermédias adaptatifs (AHS), les systèmes d'apprentissage adaptatifs (ALS) ont un point commun. Elles focalisent sur les stratégies, voies/méthodes d'enseignement, de tutorat et d'adaptation d'apprentissage ; elles ne conduisent pas nécessairement à un meilleur apprentissage du fait de l'accent mis principalement sur les outils technologiques au détriment de l'aspect pédagogique (Hrich, Lazaar & Khaldi, 2019). Le modèle didactique classique de l'environnement d'apprentissage adaptatif, est lié à l'étude de la transposition des connaissances, des enseignants et des apprenants. Rappelons que les fonctions des enseignants comprennent la conception pédagogique, l'instruction, l'évaluation, le suivi, le diagnostic, l'évaluation, la planification des parcours d'apprentissage. Ces fonctions comprennent aussi l'enregistrement, l'ajustement du contenu d'apprentissage, les recommandations et commentaires sur les stratégies adaptatives. Il est aussi important de préciser qu'un autre pan de ces fonctions consiste à définir les principes et les règles d'accès au modèle de connaissances du domaine en fonction des informations des modèles d'apprenants, et mettre à jour la conception des activités d'apprentissage au regard des objectifs d'enseignement, des types de connaissances et de l'historique d'apprentissage.

Dans le modèle d'innovation pédagogique, il est important de redéfinir, refléter les rôles et les impacts des pédagogues. La technologie adaptative vise à améliorer l'apprentissage avec une approche transdisciplinaire pour générer un apprentissage efficace. Ceci nous conduit à nous poser plusieurs questions à ce sujet.

- Quelles stratégies, méthodes, techniques et outils didactiques innovants peuvent convenir à la construction d'un apprentissage adaptatif pour les matières STEAM ?
- Qu'en est-il de l'intégration de l'analyse d'apprentissage adaptatif et du modèle d'évaluation dans un environnement d'apprentissage adaptatif pour permettre une analyse d'apprentissage en profondeur et une évaluation efficace avec l'analyse descriptive, l'analyse diagnostique, l'analyse prédictive, l'analyse prescriptive, l'analyse cognitive, l'évaluation formative et sommative pour réfléchir sur l'apprentissage performances, qualité et impacts.
- Quel modèle auxiliaire métacognitif adaptatif et quels mécanismes de rétroaction pourraient être mis en œuvre dans un environnement d'apprentissage adaptatif ?
- Quelles sont les logiques de faisabilité, de viabilité, de durabilité à prendre en compte pour être prises en compte dans le contexte de l'industrie et de la société 5.0.
- Comment des activités d'apprentissage en profondeur adaptatif pourraient être conçues pour inciter l'apprentissage autonome, l'apprentissage actif et la réflexion en profondeur afin de permettre aux apprenants de cultiver l'intelligence entrelacée pour devenir l'expert du domaine intellectuel.
- Est-il possible d'intégrer le modèle d'apprentissage basé sur les compétences ou l'intelligence dans un environnement d'apprentissage adaptatif pour la formation de professionnels de la formation professionnelle et d'innovateurs de carrières sociales ?

1.3.4 Moteur d’adaptation

Le moteur adaptatif est adapté à l'investigation dans le cadre d'un système de *e-learning*. Il joue un rôle fondamental dans l'approche individuelle des systèmes d'apprentissage adaptatifs personnalisés (El Guabassi et *al.,* 2018). Le moteur d'apprentissage adaptatif analyse les données du module de l'apprenant, diagnostique et surveille le comportement de l'apprenant en conjonction avec les données du module de connaissances du domaine. Il enrichit le matériel et les concepts d'apprentissage du module de connaissances du domaine et adapte les concepts et les règles du module pour influencer l'apprentissage des élèves (Shaky & Badawi, 2018). Dans le processus de recommandation, le module d'apprenant et le module de domaine de connaissances sont utilisés comme base pour recommander des parcours d'apprentissage appropriés en fonction de l'état d'apprentissage actuel de l'apprenant et présenter des objets de ressource personnalisés ou d'apprentissage en conséquence. La recommandation effective d'objets de connaissance est liée à la valeur de correspondance d'association des modules d'apprentissage. Le moteur d'apprentissage adaptatif définit des règles d'appariement d'association en fonction du style d'apprentissage de l'élève et de l'objet de connaissance, du niveau cognitif de l'élève et du niveau de difficulté de l'objet de connaissance. L'approche de personnalisation du moteur adaptatif utilise les profils de difficulté et de style des objets d'apprentissage de la connaissance du domaine pour correspondre au profil de l'apprenant. En enregistrant les questions d'évaluation de chaque savoir de la tâche d'apprentissage, on mesure la maîtrise des connaissances des élèves, ce qui fournit une référence pour la construction de modules d'apprentissage. Le moteur adaptatif est basé sur la base de données de contenus d'apprentissage, la base de données de stratégies d'enseignement et la base de données de ressources d'apprentissage. Il appelle les informations de connaissances descriptives enregistrées dans la base de données de contenus d'apprentissage en fonction des besoins des apprenants, y compris les noms de points de connaissance, les descriptions de connaissances, les chemins de ressources, numéros d'exercices. Sur la base des relations entre les connaissances et les facteurs de difficulté des connaissances enregistrées dans la base de données des stratégies d'enseignement, le moteur adaptatif fournit des solutions pédagogiques adaptatives pour les étudiants et les enseignants. Le moteur adaptatif fournit aux étudiants et aux enseignants des solutions pédagogiques et des parcours d'apprentissage adaptés. La recherche sur le module de moteur adaptatif se limite à la conception de systèmes d'apprentissage adaptatif basés sur la matière. Les sources d'adaptation du moteur adaptatif comprennent l'adaptation de contenu, l'adaptation d'évaluation et l'adaptation séquentielle, et l'apprentissage adaptatif est constamment mis à jour en fonction de la distance de la situation d'apprentissage adaptatif. Les futures directions de recherche pour les systèmes de moteur d'apprentissage adaptatif sont : l'apprentissage adaptatif basé sur l'apprentissage croisé impliquant l'intégration de ressources multidisciplinaires et de systèmes interdisciplinaires ; apprentissage adaptatif basé sur le développement de la théorie de l'intelligence multiple, axé sur l'analyse des données potentielles des étudiants et l'évaluation, l'orientation et l'inspiration complètes. L'apprentissage adaptatif est aussi basé sur le développement d'une littératie innovante, axé sur le développement d'aides métacognitives et de modèles d'analyse et d'évaluation de l'apprentissage adaptatif, et la construction de mécanismes de rétroaction.

Dans la section suivante nous explicitons notre réflexion des problèmes de recherche selon quatre dimensions. La dimension de l'épistémologie : réflexion sur l'innovation, la diffusion et la transformation de l'ingénierie des connaissances. La dimension de l'apprentissage : réflexion sur les méthodes de construction de modèles auxiliaires métacognitifs. La dimension didactique :

réflexion sur la qualité des modèles d'évaluation des apprentissages adaptatifs personnalisés. La dimension de la pédagogie : mesures d'impacts, de faisabilité et de durabilité.

1.4 Objectifs et questions de recherche

Cette recherche est basée sur le cadre du paradigme de l'éducation 5.0 dans le contexte de l'industrie et de la société 5.0 avec les objectifs dans l'équilibre des exigences des personnes, de la technologie et de l'innovation des connaissances. Afin de contribuer à des besoins et des objectifs de recherche plus approfondis, nous réfléchissons aux problèmes des mécanismes adaptatifs en écologie de l'éducation, y compris la gestion, l'enseignement, les domaines de connaissances, les systèmes d'apprentissage cognitifs et adaptatifs, les modèles de référence génériques, les approches, les technologies et les outils pour améliorer l'apprentissage adaptatif en profondeur. Dans le cadre du projet Et-Lios que nous présentons ci-après, nous mesurons, selon quatre axes, la valeur et la logique des méthodes de mise en œuvre, les implications de faisabilité et de durabilité. Le premier axe de l'étude concerne la source des critères d'adaptation (modèles conceptuels ou théoriques), les types d'adaptation, les méthodes, techniques, outils et contenus liés à l'enseignement, la cognition, les systèmes de connaissance, l'analyse de faisabilité et la réflexion sur les technologies des moteurs adaptatifs. Le deuxième axe examine l'évaluation des performances basée sur des indicateurs, c'est-à-dire des réflexions sur les résultats d'apprentissage, l'efficacité de l'apprentissage et l'expérience d'apprentissage basées sur des variables de caractéristiques individuelles. Le troisième axe étudie quel type de système/écosystème d'apprentissage adaptatif et d'évaluation analytique est pratique, applicable, facile à utiliser et durable. Enfin le quatrième axe s'intéresse aux caractéristiques affectant l'efficacité, la qualité et l'expérience de l'apprentissage.

Nous présentons ici les questions de recherche.

- Question de recherche 1.

Quels sont les principes de conception fondamentaux et les pratiques sous-jacentes qui posent problème dans l'apprentissage adaptatif et quelles sont les solutions proposées pour y remédier ?

L'analyse de la littérature a montré que peu d'études dans ce domaine ont abordé les questions de conception pertinentes et d'intervention dans ces systèmes d'apprentissage contemporains. En raison de la nécessité de faciliter simultanément des objectifs multiples tels que l'enseignement de connaissances complexes à un apprenant individuel de la manière la plus efficace possible, la construction d'un environnement d'apprentissage adaptatif personnalisé est devenue plus difficile.

Ces défis sont liés au fait que les systèmes actuels sont développés en augmentant le niveau de difficulté pour s'adapter de manière cyclique aux besoins variables d'apprenants hétérogènes. Le plus difficile pour les concepteurs et les développeurs est de trouver un équilibre entre la construction d'un système d'apprentissage adaptatif avancé et la garantie que les apprenants reçoivent une évaluation et un retour d'information de qualité qui leur permettent réellement d'acquérir des connaissances et de développer des compétences.

Étant donné la rapidité avec laquelle l'innovation sociale et la technologie de l'IA évoluent, il est nécessaire de mener des recherches pour développer des principes et un soutien fondé sur des preuves et des évaluations. Pour cela, une synthèse critique d'une revue de littérature a établi l'état actuel des principales caractéristiques et techniques de conception de l'apprentissage adaptatif et du tutorat intelligent.

- Question de recherche 2.

Quelles sont les caractéristiques de conception actuellement disponibles et les potentiels sous-jacents pour construire un environnement d'apprentissage adaptatif agile hybride ?

Une investigation pour reconnaître les technologies émergentes d'IA et d'apprentissage automatique qui sont omniprésentes et peuvent promouvoir l'apprentissage permet de répondre à cette question. Nous interrogeons les caractéristiques de conception de l'apprentissage adaptatif, ses composants, et si le système amélioré intégré avec des sous-modèles pourrait améliorer la capacité d'adaptabilité et l'adaptabilité de l'apprentissage. Les modèles et moteurs traditionnels comprennent les modèles génériques tels que le modèle de l'utilisateur, le modèle de connaissance du domaine, le modèle pédagogique, le modèle de gestion pédagogique, le moteur d'apprentissage adaptatif, le modèle de présentation, les mécanismes de recommandation, de retour d'information et d'intervention. Ces technologies d'apprentissage adaptatif et ces mécanismes peuvent être intégrés dans un écosystème d'apprentissage adaptatif basé sur l'IA dans le contexte du paradigme de l'enseignement supérieur 5.0 afin d'offrir un apprentissage tout au long de la vie inclusif.

Pour répondre à cette question, nous avons examiné les avantages pratiques, les technologies d'apprentissage adaptatif actuelles et les préoccupations émergentes qui doivent être abordées pour utiliser les données et l'exploration des processus afin de faciliter l'analyse de l'apprentissage adaptatif et l'apprentissage de précision.

- Question de recherche 3 :

Comment les chercheurs, les professeurs, les concepteurs et les développeurs peuvent-ils intégrer et mettre en œuvre avec succès les technologies de l'IA pour promouvoir une éducation de qualité dans le cadre d'une innovation ouverte ?

La question proposée dans la troisième partie est de mesurer l'impact et de réfléchir aux futurs indicateurs et critères d'évaluation de l'apprentissage adaptatif sur la base de la mise en œuvre des projets existants tels que ET-LIOS. Il s'agit de savoir comment améliorer les expériences d'apprentissage adaptatif personnalisées et axées sur les services, sur la base de cadres de recherche théoriques et de preuves empiriques antérieurs. En ce qui concerne la mesure de l'impact de la mise en œuvre du projet, il s'agit d'évaluer l'efficacité de la conception de l'apprentissage, la performance du processus d'apprentissage et le potentiel d'intégration des compétences professionnelles. Nos investigations sont fondées sur des preuves et fournissent une expérience réflexive pour la mise en œuvre de projets futurs et la conception de systèmes.

- Question de recherche 4.

Quels composants, variables et impacts devraient être mesurés et évalués lors de la conception d'un environnement d'apprentissage adaptatif ?

Cette question vise à vérifier l'apprentissage et les théories sur la base des preuves dans l'environnement d'apprentissage authentique. Les données d'apprentissage recueillies dans le cadre d'un module du projet Et-Lios, analysent et évaluent le type de méthodes, de techniques et d'outils d'adaptation utilisés pour évaluer l'efficacité, la faisabilité et la durabilité du point de vue de l'innovation en ingénierie didactique. De nombreuses questions, que nous posons ci-après, interrogent tout à tour les protocoles d'apprentissage adaptatif, les paramètres d'analyse de l'apprentissage adaptatif, les indicateurs, les variables, les types de données et les résultats de l'apprentissage. La collecte de données basée sur les variables personnalisées est-elle utile pour mesurer l'efficacité et l'impact de l'apprentissage ? Comment la base logique de l'analyse de l'apprentissage, des techniques d'exploration des données, de l'évaluation automatisée et du retour d'information formatif a-t-elle été prise en compte ? Comment le contenu du programme, le soutien à l'apprentissage, le retour d'information et les mécanismes d'intervention peuvent-ils être conçus sur la base de ces types de sources de données et de résultats d'apprentissage ? Et comment les caractéristiques d'adaptabilité et les dispositifs d'évaluation améliorent-ils l'efficacité des futures activités et séquences d'apprentissage adaptatif ? Enfin, quelles sont les implications pour l'adaptabilité de l'apprentissage de la prise en compte de l'analyse personnalisée de l'apprentissage adaptatif ?

Cadre général du projet de recherche

La nouvelle révolution industrielle et la transformation numérique dans le contexte de l'épidémie de COVID-19 affecte tous les secteurs concernés, y compris l'enseignement supérieur, les institutions de recherche, et ce changement est inévitable. Selon l'Organisation des Nations Unies pour le développement industriel (2021), la quatrième révolution industrielle est la clé de la transformation numérique de la société. L'enseignement supérieur et la recherche réfléchissent à l'impact des innovations pédagogiques, favorisent une éducation attrayante et valorisante mieux adaptée au développement des individus et de la société, et des expériences d'apprentissage tout au long de la vie.

La transformation numérique modifie le contenu, les outils et la pédagogie de l'enseignement supérieur. L'évolution des algorithmes, de l'intelligence artificielle et des plateformes numériques transforment les rôles respectifs des enseignants et des apprenants, et le développement des formations.

La spécificité des filières techniques et la nécessité d'utiliser des machines et équipements à caractère industriel rendent la question de l'intégration curriculaire cruciale et très influente. Le Plan d'Investissement d'Avenir (PIA3) de l'Agence Nationale de la Recherche (ANR) vise à renforcer économiquement les efforts de recherche et d'innovation. Il se concentre sur deux vecteurs de transformation économique et sociale : la transition vers un monde numérique et le développement durable. A travers le PIA3, le pays investit dans la préparation de l'avenir et soutient le développement d'initiatives nationales qui conjuguent programmes de recherche d'excellence et formations innovantes. Le plan d'investissement d'avenir permet de financer des équipements dédiés à la recherche fondamentale, soutenir des équipements directement liés à la transition numérique, et l'avancement de l'enseignement et de la recherche. L'objectif de ce PIA est de mener des projets de recherche qui élargissent l'innovation pédagogique, intègrent la recherche scientifique et technologique dans l'enseignement supérieur. La finalité est d'ouvrir de nouvelles voies pour gérer et promouvoir le développement, la démonstration et le financement de domaines innovants.

Le projet Et-Lios

Ce chapitre présente l'environnement dans lequel s'inscrit cette recherche. Il s'agit de positionner clairement la recherche empirique descriptive menée dans le cadre du projet de recherche-développement qu'est Et-Lios (Enseignements Technologiques de niveau Licence Ouverts pour une industrie du futur compétitive et Soutenable). Comme nous l'évoquions en introduction, cette recherche de thèse s'inscrit dans le cadre du projet ET-LIOS. Porté par un consortium de 14 universités françaises ce projet fait partie des lauréats de l'appel à projet "Hybridation des formations de l'enseignement supérieur" dans le cadre du Programme d'Investissement d'Avenir (PIA) de l'Agence Nationale de la Recherche (ANR). ET-LIOS est donc un projet d'hybridation des formations d'enseignement supérieur dédié à l'Industrie du Futur. La spécificité des enseignements technologiques et le besoin d'accéder aux machines et équipements à caractère industriel rendent l'enjeu de l'hybridation des enseignements crucial et impactant.

L'objectif de ce projet est de faire collaborer des ressources humaines, des enseignants, des formateurs, des chercheurs en innovation pédagogique, des ingénieurs et des développeurs, afin de fournir des plateformes et des ressources numériques appropriées. Cette synergie a pour but de favoriser la fusion de l'enseignement et de l'apprentissage, en mobilisant les parcours d'apprentissage adaptatifs et le soutien à distance et en présentiel. Dans notre recherche, nous avons envisagé un changement de paradigme dans l'organisation et la pratique de l'enseignement et de l'apprentissage, en intégrant une conception d'environnements d'apprentissage adaptatifs (EAA) pour permettre de réguler de manière flexible les modèles d'apprentissage.

Sur une période de 18 mois, le projet ET-LIOS visait à fournir, mesurer et faciliter les contenus éducatifs partagés ouverts pour l'industrie du futur autour de quatre sous-projets d'éducation hybrides impliquant une infrastructure informatique de ressources logicielles partagées virtualisées, soutenues et gérées par des centres régionaux, et soutenant la mise en œuvre de différents modules éducatifs. Le développement de cette infrastructure numérique ouverte et partagée permet d'assurer la virtualisation et l'hébergement de contenus éducatifs à travers les solutions logicielles, les plateformes et les applications éducatives. La finalité de ce projet est aussi de construire, développer et déployer du contenu éducatif et de mesurer la performance et l'impact sur les formations ciblées ; et sur la diffusion de contenus éducatifs. Ainsi, afin de favoriser l'autonomie de l'apprenant et de valider l'efficacité d'un enseignement et d'un apprentissage innovants, le projet d'ET-LIOS intègre des contenus pédagogiques élaborés conjointement par des enseignants, des chercheurs, des ingénieurs, des développeurs et des apprenants au travers de consortiums pédagogiques en expérimentation, et rend ce contenu pédagogique partagé disponible et accessible aux membres de S.mart et aux participants académiques internationaux.

Dans ce contexte l'activité du chercheur associé à ce projet relève de postures différentes, celle d'un ingénieur de conception et celle d'un chercheur visant à décrire et comprendre les usages d'un écosystème d'apprentissage adaptatif *in situ*. Rappelons ici que notre revue de littérature a mis en lumière l'absence d'un savoir unifié ainsi qu'une pluralité de discours.

Comme nous l'avons évoqué, le premier objectif de notre recherche a donc été de participer à la conception d'un modèle d'écosystème d'apprentissage adaptatif à partir des données issues de la recherche, d'analyser la coopération dans la mise en œuvre de l'innovation pédagogique et de déterminer comment les professeurs peuvent sélectionner les stratégies et méthodes de diffusion de contenu pédagogique appropriées. Il s'agissait de réfléchir aux systèmes d'apprentissage adaptatifs qui répondent aux besoins individualisés des apprenants dans une perspective multidimensionnelle tout en mettant en œuvre des tests pour vérifier l'efficacité de l'apprentissage et mesurer son impact. Ce premier travail de recherche a contribué à la conception d'un environnement d'apprentissage innovant qui s'adapte aux besoins différenciés des apprenants afin d'atteindre des objectifs éducatifs ciblés. Ce travail en phase de conception a aussi permis la réalisation de dispositifs informatiques permettant le tracé automatique du parcours d'apprentissage.

Le second objectif de notre recherche fut : i) questionner les environnements numériques d'apprentissage en phase de conception, ii) tester leur robustesse lors d'une utilisation *in situ* et iii) mesurer l'impact sur l'apprentissage. Comment les apprenants s'adaptent au nouvel environnement d'apprentissage et développent leurs compétences ? Cette étude nous a permis de comprendre les différents aspects de l'apprentissage et d'améliorer les pratiques pédagogiques en s'appuyant sur un solide corpus de connaissances. Cette étude explore plus précisément l'application du système d'apprentissage adaptatif 4.0 et des nouveaux concepts de conception dans une vision de la société 5.0.

L'étude de méthodes et d'outils pédagogiques d'évaluation et de mesure de l'impact d'environnements éducatifs innovants sur les résultats d'apprentissage, s'est appuyée sur des modèles étudiés dans l'état de l'art. Les méthodes et outils numériques de recueil de pistes pour élaborer et analyser des scénarios d'apprentissage ont été développés. Ainsi, l'analyse qualitative et quantitative des traces des élèves (*learning analytics*) a permis de détailler les différentes stratégies utilisées dans ce milieu et de générer des patterns (*process mining*).

1.5 Méthodologies de recherche

Comme nous l'évoquions en introduction, notre recherche se situe dans le cadre du laboratoire "Éducation - Formation - Travail - Savoir" plus précisément dans l'entrée 1 « Genèse des savoirs dans les institutions didactiques et apprentissages ». Du point de vue méthodologique, nous travaillons à confronter les manières dont les « phénomènes didactiques » sont produits au sein des différentes orientations scientifiques (quelles sont les méthodes mobilisées ? Que supposent-elles ? Comment articulent-elles des échelles différentes d'analyse ?). Une focale spécifique est mise sur les recherches de type participatif (quelles formes prennent-elles ? Avec quels acteurs sociaux ?) et collaboratif, notamment sous l'angle de l'articulation recherche-formation. Ainsi, c'est au sein du groupe de recherche pluridisciplinaire[14] (SGRL) que nous avons déployée une méthodologie sur mesure (Galaup, 2020). Les évaluations ont pour finalité une lisibilité "logiciel métier" en termes d'utilisabilité et d'intérêt pédagogique, en gardant la cohérence du parcours d'apprentissage de l'étudiant. Dans le cadre de ce projet, il était important de pouvoir tirer des leçons des axes de mobilisation des formations numériques et de fournir des indicateurs sur la qualité des formations technologiques proposées par la communauté S.mart. La qualité des cours peut être appréciée de manière multidimensionnelle par définition : assiduité, appréciation de l'utilité pédagogique et de l'impact des ressources proposées, ainsi que l'acceptabilité, l'attractivité et la perception des plus valorisants, puisque ces critères conditionnent de manière potentielle, l'utilisation effective de tout ou partie de la configuration d'enseignement à distance. L'évaluation d'impact se présente comme un axe horizontal mais central de la mission du projet, apportant une cohérence et une meilleure viabilité à toutes ces ressources très hétérogènes qui ont été créées pour faire face aux situations de confinement : sessions virtuelles jumelées, pilotes de logiciels à distance, webinaires, vidéos, questionnaires en ligne, etc. L'objectif de cette tâche de mesure de l'impact est double. D'une part, fournir un référentiel commun permettant d'évaluer l'ensemble de ces initiatives, malgré leur nature différente, à travers des critères objectifs et comparables. D'autre part, l'objectif était d'apporter un soutien à la production d'outils d'évaluation au cas par cas, en tenant compte de la spécificité de chaque ressource. Le projet soutient des méthodes quantitatives en mettant en œuvre une évaluation par la collecte et l'analyse de traces d'utilisateurs dans des cas possibles (par exemple, des laboratoires virtuels, des événements numériques interactifs, etc.). Dans d'autres cas, un outil d'analyse qualitative est proposé, en plus des activités de collecte des données nécessaires à l'évaluation, dans le but de comprendre et de mesurer la performance et l'impact du programme dans le contexte de la formation. Plus précisément, mesurer l'impact

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[14] Groupe de Recherche Pluridisciplinaire INU Champollion : ***https://www.univ-jfc.fr/grp/serious-game-research-lab-sgrl***

signifie mesurer les effets sur les étudiants des nouveaux supports de cours dispensés dans le cadre de l'enseignement mixte. Ces conséquences peuvent être psychologiques, sociales ou encore impacter l'apprentissage. Pour cette raison, nous avons travaillé avec différentes universités partenaires pour développer des supports de cours interactifs qui respectent les contraintes liées au contenu de chaque module et les protocoles établis par les enseignants. Ces supports permettent de suivre automatiquement les indicateurs à chaque utilisation. Ainsi, les mesures réalisées permettent de s'assurer de la qualité de l'accompagnement et des activités fournies, et d'identifier les axes d'amélioration.

Les principales contributions de notre méthodologie proviennent de la conception, de l'analyse et de la mise en œuvre minutieuses des expériences, ainsi que du suivi, du rapport et de l'évaluation furtifs et approfondis des résultats quantitatifs des expériences, en se concentrant sur les aspects de l'expérience d'apprentissage, de l'impact et de la durabilité lorsqu'évaluer l'offre de différentes formes d'adaptation. Lors de l'évaluation de l'efficacité et de l'impact de l'apprentissage, trois principaux facteurs sont pris en compte : la progression de l'apprentissage, la motivation et l'engagement. Les résultats expérimentaux peuvent fournir plus de preuves de l'importance de la personnalisation et de l'adaptation des matériels d'apprentissage et de leur séquençage pour répondre aux divers besoins des différents apprenants autorégulés dans les systèmes d'apprentissage en ligne.

Nous pouvons retenir trois contributions innovantes de cette méthodologie :

• Contribution 1 : conception expérimentale et le développement de l'application d'apprentissage permettant i) de s'adapter aux besoins d'apprentissage de chaque apprenant, ii) une mémorisation des trajectoires d'apprentissage, iii) de fournir des rappels d'oubli basés sur les erreurs commises à partir des travaux pratiques.

• La contribution 2 : réalisation d'expériences pour suivre et analyser furtivement les données de trajectoire d'apprentissage, tout en ajustant de manière adaptative les activités et la difficulté. Proposer des stratégies, des commentaires cognitifs et métacognitifs supplémentaires chaque fois que cela est nécessaire.

• La contribution 3 : le travail d'évaluation sur l'analyse de l'apprentissage qui a été utilisé pour évaluer l'impact, à l'aide de mesures standard, et pour étudier la relation entre les expériences des utilisateurs telles que le sentiment perçu de convivialité, d'utilité, d'acceptabilité, d'attractivité et d'apprentissage performance.

Ainsi, dans le cadre de la contribution 1, nous avons conçu une application informatique capable de corriger le travail des étudiants et de leur fournir un retour personnalisé. Elle permet à l'enseignant de mieux suivre ces retours, l'élève peut essayer autant de fois qu'il le souhaite et apprendre de ses erreurs, tout en se concentrant sur les consignes fournies par le compagnon numérique intégré à l'activité. Une autre application conçue permet, par exemple, à l'étudiant d'assumer le rôle de correcteur en évaluant le travail de ses pairs, dont le propre travail est également évalué par eux. Ce processus, appelé évaluation par les pairs, permet aux élèves d'apprendre de leurs propres erreurs ainsi que de celles des autres. Une fois leur travail et leurs corrections terminés, les étudiants passent à la phase d'autocorrection où ils peuvent réviser leurs propositions en tenant compte des commentaires de leurs pairs. Dans le cadre de nos activités de recherche, nous participons au développement de logiciels de simulation basés sur la technologie du jeu vidéo, tels que la Maison Virtuelle HOME I/O ou la Usine Virtuelle FACTORY I/O. Grâce à ces outils de simulation, les étudiants peuvent effectuer leur travail réel à distance dans un environnement amusant. Les outils fournis facilitent l'apprentissage, notamment la validation en ligne de l'efficacité des actions entreprises par les apprenants.

Selon la contribution 2 de notre méthodologie, nous avons proposé une expérimentation pour suivre et analyser furtivement les données de trajectoire d'apprentissage. Un test pilote a été réalisé avant l'expérience. Les principaux objectifs de ce test étaient de vérifier la faisabilité des conditions de l'expérience, les problèmes techniques liés au système développé, la fiabilité et la cohérence de la collecte de données, le niveau de difficulté du matériel d'apprentissage, la durée et les problèmes de l'expérience.

Nous avons privilégié une approche quantitative en mettant en place une évaluation basée sur la collecte et l'analyse des traces des utilisateurs (par exemple, des laboratoires virtuels, des activités numériques interactives, etc.). Des outils d'analyse qualitative sont proposés en complément des activités de collecte des données nécessaires à l'évaluation ; en présentiel ou à distance : prise en charge des rappels de cours, des exercices d'apprentissage, des sujets de TP et des fichiers de configuration. Le développement d'activités et d'outils pédagogiques pour compenser l’absence de l’enseignant et donc moins de suivi : développement d'outils permettant la vérification par les élèves de leurs solutions. Le développement d'un générateur automatique de canevas pour un automate programmable industriel (API) afin d'améliorer l'interface d'apprentissage. Enfin, le développement et/ou utilisation d'outils gratuits[15] sur smartphone pour révisions et/ou vérification des prérequis.

Notre hypothèse est que tous les étudiants étaient à un niveau cognitif similaire et que les paramètres de collecte de données devaient évaluer de manière invisible leur performance et leur qualité dans les activités pratiques, y compris le nombre de fois qu'ils ont appris, le nombre de tentatives, le nombre de tentatives avant le succès, oublis et/ou tentatives d'erreurs. Les critères du mécanisme d'évaluation ont été définis comme étant le groupe qui a obtenu de meilleurs résultats en apprentissage, le groupe qui n'a pas eu de difficultés d'apprentissage, le groupe qui était à risque en apprentissage et les élèves qui ont manqué des classes. Les données obtenues et les résultats de l'analyse sont présentés et discutés. Nous revenons également sur la manière dont une analyse plus approfondie peut être effectuée pour évaluer la probabilité que les apprenants maîtrisent l'apprentissage et l'acquisition de compétences, quelles méthodes, techniques et outils sont applicables. La base logique de l'utilisation possible d'une rétroaction et d'interventions améliorées dans la pratique de l'enseignement comprend la valeur, la faisabilité et la durabilité. Nous proposons une méthode de travail basée sur le travail de groupe déjà mis en place pour garder les apprenants motivés.

Les objectifs et les questions abordés dans cette partie sont basés sur les données d'apprentissage recueillies dans le cadre du module D du projet, analysant et évaluant le type de méthodes, de techniques et d'outils d'adaptation utilisés pour évaluer l'efficacité, la faisabilité et la durabilité d'une innovation en ingénierie didactique. Cela implique des problèmes tels que les protocoles d'apprentissage adaptatif, les paramètres d'analyse de l'apprentissage adaptatif, les indicateurs, les variables, les types de données et les résultats d'apprentissage. La collecte de données basée sur l'historique d'apprentissage est-elle utile pour réfléchir sur les progrès de l'apprentissage et aider à améliorer la conception des systèmes d'apprentissage adaptatifs ?

1.6 Conclusion

Au terme de cette recherche de thèse réalisée dans le cadre du projet de recherche ET-LIOS de l'appel à projet "Hybridation des formations de l'enseignement supérieur" dans le cadre du Programme d'Investissement d'Avenir (PIA) de l'Agence Nationale de la Recherche (ANR) nous

[15] Les participants à la conception expérimentale des sujets de recherche sont le pôle Nord Pas de Calais (UPHF) et Univ. Reims Champagne Ardenne (URCA). Nous avons collaboré avec le module URCA D- Jumeau numérique et virtual commissioning pour la production automatisée, et le cours ayant bénéficié d'un accompagnement et d'une évaluation de conception d'outil pédagogique était Logique Combinatoire Numération Codage.

souhaitons revenir sur certains points relatifs aux EAA. Rappelons que notre projet de recherche concerne la construction d'un écosystème d'apprentissage adaptatif personnalisé. Cet exercice a nécessité une conception d'un EAA qui a nourri une collecte et une analyse des données en fonction du profil de l'étudiant, notamment une analyse descriptive, diagnostique, prédictive, prescriptive et cognitive. Les résultats de ces analyses des données d'apprentissage ont permis de revenir sur la conception adaptative de l'enseignement, d'améliorer sa qualité et de renforcer ses effets. Ces résultats éclairent les trajectoires différentielles des apprenants toujours singulières. L'ensemble des résultats produits par ce travail nous a permis d'étudier, selon une double posture, les effets de la mise en œuvre d'un EAA et certains aspects de la conception. Notre approche multi-domaines, nous a permis d'identifier plusieurs critères et catégories et de voir comment ils peuvent être combinés pour produite une intelligibilité des EAA.

Cette thèse a contribué à comprendre un écosystème d'apprentissage adaptatif dynamique en l'établissement un ensemble de références et de propositions pour leur construction et la mesure de leurs impacts. Nous avons effectué une revue de la littérature concernant l'exploration des bases théoriques, des définitions, des caractéristiques de conception et des techniques relatives à l'apprentissage adaptatif. Un examen complet des références théoriques (Cf. chapitre 2) et de la définition de l'apprentissage adaptatif (Cf. chapitre 3) a permis de comprendre le contexte et ses limites. Ce travail a permis d'établir une taxonomie de l'apprentissage adaptatif sur la base de l'exploration d'analyses et d'études antérieures. Ainsi, ont été examinés les caractéristiques de conception de l'apprentissage adaptatif, des systèmes de tutorat intelligents et les éléments d'adaptation correspondants dans les modèles pertinents (Cf. chapitre 3). Un cadre de référence pour l'analyse de l'apprentissage multimodal a été proposé, (Cf. chapitre 4) offrant la possibilité de concevoir, d'évaluer et de comparer les systèmes et les techniques utilisés dans leurs projets. Ce travail est exposé plus en détail dans Huibin et Galaup (2023).

L'étude de la construction d'environnements d'apprentissage adaptatifs (EAA) et la mesure de l'impact nous a permis de proposer une réflexion sur les ingénieries pédagogiques et les expérimentations de ces nouveaux dispositifs didactiques. Ce travail propose des recommandations, il pointe notamment l'absence de couplage entre les théories de l'apprentissage, les types de connaissances et les caractéristiques de l'apprenant lors de la construction d'un apprentissage adaptatif intégré dans une salle de classe. Il est apparu des faiblesses au niveau des analyses plus approfondies, notamment au niveau des besoins en compétences du 21e siècle, de l'expérience des utilisateurs, des ressources disponibles et de la prise en compte du point de vue des utilisateurs. Nous soulignons la nécessité de renforcer le développement d'une vigilance épistémologique et cognitive permettant notamment d'avoir une meilleure maitrise de données issues de l'IA générative. Le traitement des questions de cybersécurité et de confiance doit aussi être pris en compte afin de faciliter la transformation de l'apprentissage adaptatif.