Evaluation of a Computer-Assisted Language Learning System Based on Adaptive Learning Designed for Self-training in Scientific French Language

Sara Ouald Chaib*, Imane Joti, and Samira Khoulji

***Abstract*—This article presents the development and evaluation of a computer-assisted language learning system designed for self-training in scientific French language. The main problem addressed by this research is the linguistic obstacles faced by students during their academic years, which inspired the implementation of an adaptive learning system personalized to their needs. The methodology applied involved a need analysis approach to better adapt the French language learning offer to students' demand, followed by the development of an adaptive learning model based on Item Response Theory (IRT). The system was evaluated by the System Usability Scale (SUS) model which shows high usability and user satisfaction and engagement. The findings were very encouraging, demonstrating that the presented adaptive learning model improves the adaptability of students' needs and preferences. Overall, the aim of this research is to prove that the proposed learning system will improve the learners' performance and understanding of scientific French language.**

***Index Terms*—Self-training, personalization, adaptive learning, item response theory, adaptive spacing system**

I. Introduction

In education, it is important to understand and to design the content learning according to the state of perception of each learner. In recent years, digital education has become one of the relevant issues in the scientific literature, which has involved the production of computer programs that aim at aiding students to acquire concepts and know-how. We are talking about Intelligent Tutorial Systems (ITS). ITS are adaptive educational applications that enrich the tutoring and learning processes with "intelligence" by revealing the capacities and weaknesses of each learner. They are divided into four modules: the expert system, the tutor system, the graphical interface, and the learner model. The latter is the module responsible for offering customization.

Dooly has shown in his experiment on "students' innovative use of technological resources in the language of classroom that the act of modeling learners is able to highlight their individual needs, learning characteristics, level of knowledge, errors or misconceptions, etc. [1].

Today, it is seen that ITS have been used to teach a variety of areas of knowledge. When it is used to teach and learn a foreign language, a new field of research has arisen; it is called Intelligent Computer-Assisted Language Learning (ICALL). ICALL involves the application of computer technologies, such as artificial intelligence and multi-value logic to promote digital education [2].

In Morocco, French is the language of instruction in science university faculties. This imposes accentuated linguistic difficulties for most students who have taken Arabic courses. So, the foreign language process can be influenced by languages the learner has already learned. Despite the comprehensiveness of platforms and digital applications dedicated to self-training and self-correction in terms of the development of linguistic and pragmatic skills, there are still difficulties related to the various constraints in terms of timetables, heterogeneity of levels, places, workforce, support etc. [3].

Due to these difficulties, most teachers tend to use similar teaching approach and rate of progression. Working with a large number of students with the same materials or same methods signifies that students with higher levels of competence are limited by the pedagogical progress imposed by teachers, and therefore cannot effectively manage class time for learning. On the other hand, students with insufficient skill levels may not be able to understand the course content which would consequently result in difficulty to consider the learning needs of each student.

In this context, the researchers proposed a student-centered adaptive learning model; it is a model that considers the individual differences of students in the design of learning materials so as to obtain better learning outcomes [4].

Several researchers have started to develop such adaptive learning systems using Artificial Intelligence (AI) technologies to provide guidance, personalized learning aids and supports for individual students in various courses, such as computer programming [5] and mathematics [6, 7]. Therefore, the results proved the effectiveness of this kind of systems in different fields, with the help of the intelligent tutoring systems used, they improved the learning performance of the learners and increased their learning motivation. Therefore, compared to traditional computer-based learning systems, adaptive learning systems can promote students' learning performance [8].

Returning to the field of language, we notice that the ICALL system attracts the attention of many researchers because it uses intelligence to promote personalization and adaptability in digital environments for language learning. There are several studies done in this field. If we move towards the detection of linguistic errors, we note that the analysis and diagnosis of errors are an important factor in educational systems because it provides guidelines to learners in order to correctly perceive the learning objects. In this direction, Cowan *et al*. [9] presented an ICALL app that

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S. Ouald Chaib, I. Joti, and S. Khoulji are with the National School of Applied Sciences, Tetouan, University Abdelmalek Essaadi, Morocco.

*Correspondence: sara.oualdchaib@etu.uae.ac.ma (S.O.C.)

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attempted to empower learners to recognize and understand their mistakes, and practice correcting them. On the other hand, Wu *et al*. [10] suggested methods to effectively correct errors and use learning strategies. Through their approach, they tried to improve students' writing abilities and develop their learning skills and strategies. Chen *et al*. [11] presented their model for diagnosing grammatical errors. Their model involved a rule-based method and an *n*-gram statistical method to detect grammatical errors, identify the type of error, and detect the position of the error within sentences.

However, after an extensive search in related scientific literature, we concluded that there is no adaptive machine learning based model designed from taught programs to identify learners' linguistic errors within Moroccan scientific university faculties. Therefore, we believe that the use of intelligent computer systems can overcome the linguistic difficulties of science students. On the one hand, this can affect their learning process, and on the other hand, be a solution to the constraints encountered by language teachers.

II. Research Objective

The main objective of this study is to evaluate the effectiveness of a computer-assisted language learning system based on adaptive learning for self-training in scientific French language. The idea of setting up such a system stemmed from our observations of the linguistic obstacles faced by students during their academic years at the Faculty of Sciences of Tetouan, as well as other problems concerning language training. While we found no adaptive machine learning based model designed from taught programs to identify learners' linguistic errors within Moroccan scientific university faculties, we believe that the use of intelligent computer systems can overcome these difficulties and provide a solution to the constraints encountered by language teachers. In this study, we aim to prove that such a suitable learning system proposed for foreign languages will improve the learner's performance and understanding. The system utilizes an adaptive spacing system during the learning process to optimize long-term retention of learned information, and we evaluate its effectiveness using an evaluation model.

III. Research Methodology

Under the Research Methodology section, we employed a mixed-methods research design, which combines quantitative and qualitative research methods to obtain a deeper understanding of the research problem. The study was conducted in a naturalistic setting at the Faculty of Sciences of Tetouan, where the participants were undergraduate students enrolled in the scientific streams. The sample size was 200 students, divided into two groups: the experimental group and the control group. The participants were randomly assigned to each group to eliminate any potential bias. The instruments used in this study included a placement test, a pre-test, a post-test, and a survey. The placement test was used to determine the participants' language level, and the pre-test was used to assess their initial knowledge of the French language. The post-test was used to evaluate their learning progress after using the computer-assisted language learning system. The survey was used to collect data on the students' perceptions and attitudes towards the system. The data gathering procedure included administering the placement test, pre-test, post-test, and survey to the participants. The experimental group received training using the computer-assisted language learning system based on adaptive learning, while the control group received traditional teaching methods. The study was conducted over a period of three months, and the participants were assessed regularly to evaluate their progress. For data analysis, descriptive statistics and inferential statistics were used to analyze the quantitative data obtained from the tests and the survey. The qualitative data collected from the survey were analyzed using content analysis to identify emerging themes and patterns. In terms of ethical considerations, we obtained informed consent from all participants before the study, and their anonymity and confidentiality were guaranteed. We also ensured that the study did not harm the participants in any way. The computer-assisted language learning system used in this study was based on adaptive learning, which allowed for personalized learning tailored to the participants' needs and preferences. The system used an adaptive spacing algorithm to optimize long-term retention of learned information. The system also provided feedback to the participants to correct their errors and reinforce their learning.

IV. Identifying Learner's Needs

In our study, the needs analysis process was conducted before the design of the training system. We opted for both qualitative and quantitative analysis of the data. We distributed questionnaires addressed to students, conducted interviews with both students and teachers, and we attended sessions with students in their language classes for observation.

A. Audience Description

First, it should be noted that this course is open to all first-year students of Faculty of Sciences at the university. We find an audience coming from various scientific majors (Biology, Physics, Math; experimental sciences in general) but with heterogeneous levels in French language. We have students who have taken Arabic courses, students from the Orient (Syria and Yemen) who have no previous experience in learning French, students who have an international baccalaureate; they already have the background in scientific terminology in French Language, and the same case for foreign students from South Africa (Senegal, Equatorial Guinea, Niger, Sudan, Mauritania). We are therefore dealing with participants with little or no knowledge of scientific French language and will have to face challenging and unfamiliar situations.

We summarize the characteristics of our targeted participants in the Table I below. The data is based on the observation of more than 210 Mathematical Sciences and Applications/Mathematical and Computer Sciences (SMAI) students (Semester 1) plus interviews and an established questionnaire:

TABLE I: CHARACTERISTICS OF THE TARGET AUDIENCE (JOTI & OUALD CHAIB, 2020)

Criteria	Features
Age	17–27 years old
Schooling	Fundamental Bachelor's degree (in preparation—first year SMAI (Mathematical Sciences and Applications/Mathematical and Computer Sciences))
Student audience	Moroccans and foreigners
Mother tongues of non-native students	Arab, Amazigh, Allophones (English, French, Spanish) and Sub-Saharan.
Linguistic situation of students and cognitive skills	French as a Foreign Language (FFL), French for Specific Purposes (FSP), French for Academic Purposes (FAP) and existence of pathological cases (dyslexics, cognitive disorders, etc.)
Acquired in secondary cycle	Heterogeneous CEFR levels of French language acquired in an institutional setting: Levels (A1, A2, B1, B2, C1)
Motivations	*Communes*: Take scientific courses in French that are compulsory for the university program. *Others*: Study in a French-speaking countries in Europe, participate in the Erasmus program by studying for a semester in a French-speaking university in Europe or integrate into the professional environment.
Essential objective	Develop language and communication skills in French language necessary to follow the bachelor's program in science.
Expectations	Master the speeches related to scientific fields.
Training context	-Non-French-speaking university environment. -Access to a multimedia room for tutorials and practice for the "language and terminology" module. -Interactive lectures according to the skills-based approach. -Duration of a semester: 24 one-hour sessions.

B. Hypothesis

After the observations, the next step is to define the working hypotheses and determine the research method. For this, a computerized questionnaire has been devised for first-year university science students, Semesters 1 and 2, of the Faculty of Sciences of Tetouan for the academic year 2020/2021. The questionnaire aims, on the one hand, to highlight the impact of linguistic difficulties on teaching-learning at the level of scientific sectors of the Faculty of Sciences of Tetouan (Morocco), and on the other hand, to present alternative solutions to overcome those difficulties.

It is mandatory to have students who can recognize and use the target language, as well as have the ability to adapt their linguistic repertoire to which they will have to resort when they are in learning situations in all scientific modules.

In this respect, the general hypothesis is that a good personalization will facilitate the learning process, increase the investment and motivation of learners, and can also be a decision-making aid relating to the content to be taught for teachers.

C. Research Process

To verify the general hypothesis and to be able to define the activities to be developed in our computer system, we carried out semi-structured interviews as well as a computerized research questionnaire intended for the two types of audiences:

1) Teachers of the "Language and Terminology" module.
2) Students of the Faculty of Sciences.

For these two data collection methods adopted, we focused on two main areas, namely:

Language barriers: The objective of this section is to investigate language barriers that hinder learning process in scientific fields at the Faculty of Sciences of Tetouan. Based on teachers' declarations, we managed to observe the existence of certain constraints in terms of timetables, places, numbers, heterogeneity, and support. While students complain about other problems such as: difficult scientific terminology, traditional explanation strategy adopted by teachers does not really allow effective learning, absence of communication between teachers and students, and absence of the integration of Information and Communications Technology (ICT) in teaching.

There is one difficulty commonly stated by both audiences which is the difficulty in recognizing and using words that they have already learned in the appropriate context.

Computer tools: We were able to observe that the use of computer tools is of interest to both audiences at the level of development of the linguistic skills of university students. In particular, we noticed a high level of interest in social networks and audiovisual resources among the participants at the level of training [12].

This means that working with ICT is not a new task for the majority, and the students are ready, at the level of materials and organization, to invest in training for development.

In the second part of this research, after the design phase and the development of our adaptive pedagogical model, comes the evaluation phase, which is divided into two parts. The first part is devoted to evaluating the efficiency of training and learning via monitoring students' exploitation and use of our system. The second part concerns the evaluation of the user experience in order to know the satisfaction and the motivation of the students towards our system.

D. Goals

Our objective through this section of work is to adapt the units of the course in module "language and terminology" to the profile of the learners, and to propose an adequate course for their level. The objective is also to maintain their motivation to continue their learning until the end.

V. SYSTEM OVERVIEW

The adaptive learning model presented in this study is built on a generic framework of computer-assisted language teaching methods. One such framework is the Intelligent Computer-Assisted Language Learning (ICALL) framework proposed by Levy and Stockwell [13]. The ICALL framework is based on the integration of computer technology, natural language processing, and language pedagogy to provide personalized and adaptive language learning experiences. Our adaptive learning model utilizes the principles of the ICALL framework by incorporating machine learning algorithms to adapt the content and training provided to each individual student. By leveraging the capabilities of this framework, we aim to provide an effective and efficient language learning experience for science students.

Fig. 1 shows a diagram of the framework, which is based on the Intelligent Computer-Assisted Language Learning (ICALL) framework proposed by Levy and Stockwell [13]. It is a four-layered model that aims to integrate technology and pedagogy in language learning. The four layers are as follows:

- Data layer: This layer includes the databases of linguistic resources such as grammar rules, vocabulary, and corpus-based examples.
- Processing layer: This layer deals with Natural Language Processing (NLP) tools, which are used for analyzing and generating language. The NLP tools include morphological analyzers, parsers, and generation tools.
- Pedagogical layer: This layer includes the pedagogical models for language learning, such as task-based learning, content-based learning, and communicative language teaching.
- User interface layer: This layer includes the interface design for language learning, such as multimedia content, visual aids, and interactive exercises.

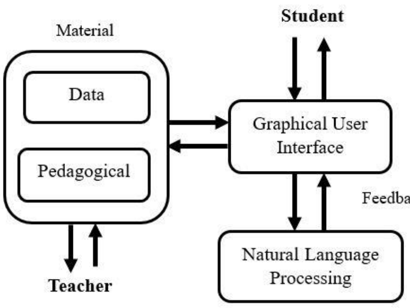


Fig. 1. Diagram that illustrates the generic framework of computer-assisted language teaching methods proposed by Levy and Stockwell [13].

Levy and Stockwell [13] proposed that the integration of these four layers would lead to the development of more effective and personalized language learning tools.

To successfully develop language proficiency, the activities made available to students must take place in an authentic and motivational context and according to their educational needs, their levels of understanding of the subject, and their ways of learning. To do this, we have adopted the adaptive learning method, which makes it possible to personalize teaching according to the mode and pace of learning specific to each individual. Adaptation to the learner can be done through individualized learning or personalized learning [14].

As we have already defined adaptive learning as the process of "building a model of the learner's goals, preferences and knowledge, and using it throughout their interaction with the environment in order to offer personalized feedback or to adapt the content and the interface to their learning needs" [15]. It corresponds to a sequencing of the course according to the answers of the learners.

A. Adaptation Mechanism

To design a system based on adaptive learning, it should consider the cognitive state [16], which includes memory, knowledge recall, thinking, problem solving, and creating, while emphasizing that the main characteristic of knowledge is the acquisition and application of knowledge [17]. In our system, we have tried to consider these aspects such as the memorization of answers.

It is necessary to introduce all the elements necessary to improve the motivational aspect of students. in this context, Malone's theory of motivation emphasizes how to make computer-based educational activities motivating and fun using elements such as: challenge, objectives, feedback, self-esteem, curiosity, control and fantasy [18] (Fig. 2). These elements were included in the learning activities of this study; For example, the challenge element has been introduced into the tool by increasing the difficulty of educational content. In addition, the level of the latter has been adapted according to the skills of the students. Sensory curiosity was stimulated by the change and attention to the progress bar and the sound used for the various activities. For control, students take control in accomplishing their tasks and decide if they want to continue through motivating interaction.

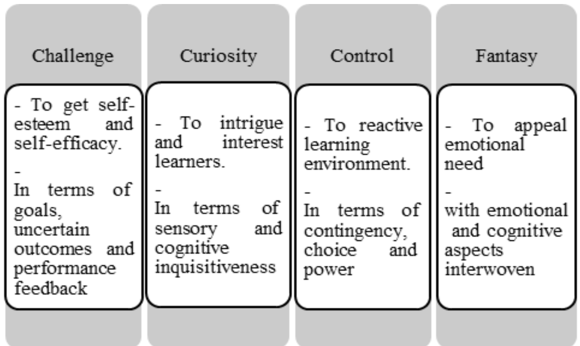


Fig. 2. Intrinsic motivators described by Malone and Leeper [18].

In addition, the system must be able to analyze the errors made by students as they will be placed at the center of the digital teaching, which considers the results of the error diagnosis to automatically model the learning process or failure of every student. Thus, their level of knowledge must be represented in a more realistic way that allows them to complete the activities at their own pace and according to their own abilities.

Therefore, we then focused on the following axes:

- **Evaluation**: understands those of the main sentences, to detect the faults of the students and direct them towards their needs.
- **Training**: includes notions that students will need to train themselves and the analysis of their progress.

The idea is to use automated exercises, such as multiple-choice questions or filling in the blanks, usually at increasing intervals, until the answer comes without reflection, since the aim to memorize long-term information. We are then in a logic of formative evaluation. The assessment serves as practice.

On the other hand, as in face-to-face teaching, self-training requires specific orientations. If it has the advantage of allowing students to adapt their learning to their own difficulties, at their own pace, it suggests that a guide can help students in this process [19]. For this, guidance was invoked in an asynchronous way to reinforce the idea that the teacher is indeed present, but not at the time of the learner's learning. Through precise instructions, Students have the possibility to contact their teachers by email which would allow students to develop their learning autonomy.

B. The Interest of a Computer Device Based on Adaptive Learning

In the field of development of linguistic skills of French for Specific Purposes (FSP) in Morocco, IT instruments such as Computer-Assisted Language Acquisition (ALAO) or also ICALL type intended specifically for an audience of students at Faculties of Sciences of Abdelmalek Essaadi University and designed based on the needs of the students do not existent. To our knowledge, there are no intelligent computing devices in this context that train students in linguistic aspects of the scientific target language in university language classes.

C. IT System Features and Architecture

The computing environment we design consists of two users' graphical interfaces [20] (Fig. 3). The first should allow students to carry out the activities that teachers will program and have access to through another graphical interface, allowing them to constitute pedagogical training sequences and to visualize the scores of the students. The system has a Database (DB) for student activities and information.

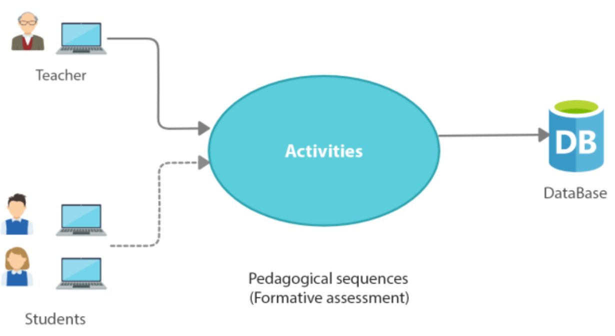


Fig. 3. General architecture of a self-training computer system.

VI. Scripting of Educational Activities

A. Didactic Sequences

We decided to build our self-training system from didactic sequences. Each one consists of three phases (Fig. 4).

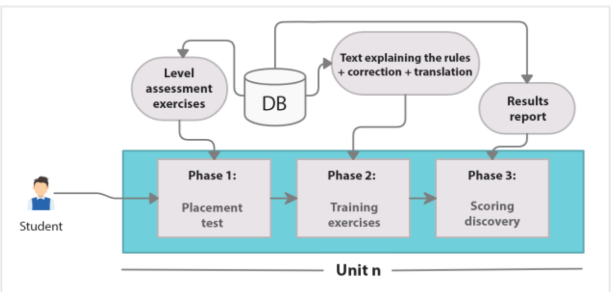


Fig. 4. Diagram representing a didactic sequence of self-training.

As we can see, in the diagram Fig. 4 above, phases 1, 2, and 3 use the DB (database of activities with the concepts to be worked on). Each phase includes different exercises or content:

- Positioning test (phase 1): assesses the level of students in relation to their prerequisites in order to offer them suitable courses and exercises to discover linguistic phenomena from different activities.
- Training exercises (phase 2): They allow autonomous learners to better understand the linguistic phenomena discovered in the previous phase. Multiple Choice Question type (MCQ-type) exercises and incomplete texts provide a fairly simple way to practice the concepts worked on during self-training process. During this important phase, for each learner, the system will make it possible to exploit, in a subtle way, the traces of the learner during the previous phase and to establish personalized training activities that are centered around the rules that the learner does not master. The program continues to adapt automatically to the learner's pace of acquisition allowing him to acquire the right automatisms.
- Score (phase 3): In this phase, students and teachers will be able to consult the scores. Teachers will have the opportunity to keep track of their students' progress.

B. Content Design

The teaching of the French language in Moroccan universities adopts the spirit of the Common European Framework of Reference for Languages (CEFRL), which offers tools for organizing the teaching-learning of languages in a specific field. It offers a common basis for the development of language programs, reference systems, examinations, and textbooks. The CEFR describes the knowledge and skills that the learner must acquire to have effective language behavior [21].

In this respect, following the consultation of the collections and the analysis of the needs of the students and teachers of the Language and Terminology department, as well as the analysis of the existing programs, we have tried to determine the essential elements and the possible structures of the digital device content to be developed.

In order to meet the needs and overcome the face-to-face constraints, comes the need to make additional remote resources available in addition to a face-to-face course. In this sense, we have prepared the pedagogical scenarios of the prototype of the PC application module, which has just completed the French textbook Cap Université[1]. This manual is intended for students at levels A1-A2, according to the CEFR classification, enrolled in semesters 1 and 2 of the Science and Technology courses and aims to bring them to level B1 at the end of the 1st university year.

It consists of eight files addressing different themes. The first and second four files cover first (48 hours) and second semester respectively. Each file contains different teaching-learning activities on written and oral documents. The idea is to use the materials in this manual to set up a self-training system to complement the face-to-face course to reach level B1 while facing the constraints already mentioned. On the one hand, this will allow to treat the files in a more exhaustive way. On the other hand, it will allow the students to work in an autonomous way.

In turn, **FLExible** (the idea of the name comes from the

[1]Manual designed and developed by university teachers (coordinators of the teaching of the "Language and Communication" modules in Moroccan universities).

composition of the following words: **F**: French, **L**: Language, **E**: Foreign, **xible**: with flexibility) (Fig. 5) consists of eight units corresponding to the themes seen in the first year of the Bachelor's degree, inspired by the Moroccan context. For example, unit 1, which is entitled: scientific disciplines and professions, is made of several activities that will allow students to discover tips for mastering the basic rules of specialized French.

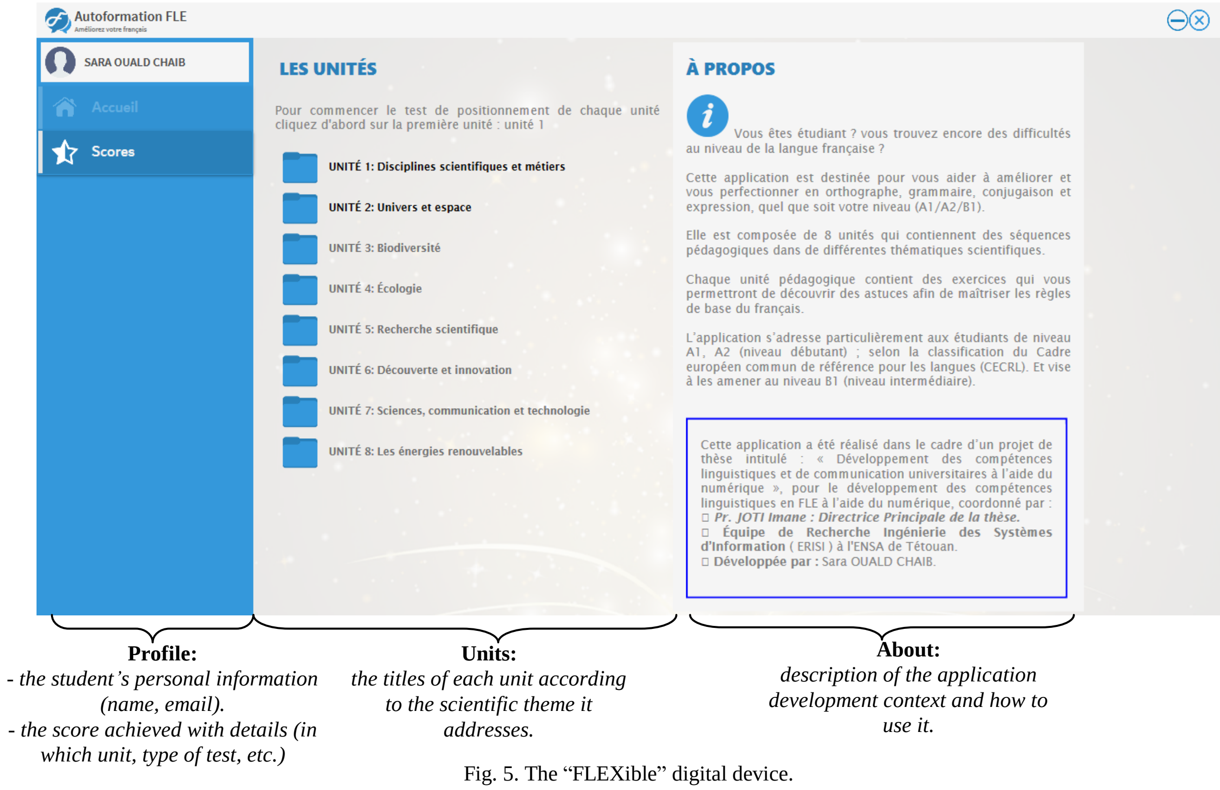


Fig. 5. The "FLEXible" digital device.

As shown in Fig. 5 above, the learning process of the FLExible digital device operates in the following order:

1) Start with a placement test to determine your level.
2) Discover your detailed test report to know the rules that require an upgrade.
3) Start training on unmastered rules with different exercises (MCQ, Fill-in-the-blank texts, etc.). Once the answer is validated, an explanation of the rule will be displayed.

When the training is finished with a score of 50%, the student can advance to the next unit. At the end of the training, they will obtain a B1 level certificate.

For the training phase, several techniques and learning methods were used to allow the student to become aware of their difficulties and to remedy them, such as:

- A repetition system that depends on the pace of acquisition of the learner to memorize the rule according to progressive intervals.
- A progress bar that enables the learners to keep track of their progress.
- Translation of scientific terminology in Arabic and English to facilitate reading for foreign students from South Africa and the Middle East. This technique facilitates the memorization of lexical fields and their grammatical forms.

VII. System Development

First, this adaptive learning module adapts the difficulty of the questions provided to the learners according to their level of knowledge by using the theory of the answer to the Question Items (IRT). It also provides rules and examples when learners fail to answer questions, and it even corrects answers to reinforce learning.

In the case of closed-ended questions of different types (multiple-choice questions and fill-in-the-blank questions), such as those used in our case, the IRT can be an interesting solution to adapt the questions to the level and skills of the students [22, 23].

The IRT is based on a probabilistic model that assumes a relationship between the validity of the learner's answer to a question on the one hand and the characteristics of the question and the learner's mastery of the concept on the other. Given a learner A_j and a question Q_i, where "i" represents the index of the question and "j" represents the index of the learner, the probability of success of the learner to the question is written Eq. (1):

$$P_i(obs=correct|A_j) = g(A_j, Q_i) \tag{1}$$

In IRT models, each item is characterized by three indices, namely the difficulty index, the discrimination index, and the pseudo-chance index. Each of these indices describes a particular property of the item with which they are associated. (These three parameters can be used to estimate the learner's ability, and thus provide students with material suited to their abilities).

There are calculation models that depend on the number of parameters; for instance, the One-Parameter Logistic Model (1PL) for the IRT; We speak of the difficulty parameter of a question which is the value that corresponds to a probability of success exactly equal to 50%. There is the Two-Parameter Logistic Model (2PL) where the difficulty parameter is always present, plus the discrimination which is its ability to differentiate individuals (distinguish those who pass the item from those who fail it). Also, there is the Three-Parameter Logistic Model (3PL); we can create that by adding the pseudo-chance parameter (γ_j) which represents the probability that a subject with very low ability will correctly answer an item j by randomly choosing one of the options offered.

For our module, we used 2PL because it is equivalent to the 3PL model or the pseudo-chance parameter ($\gamma_{j)}$, which is assumed to be zero ($\gamma_j = 0$) Eq. (2). It implies that there is no chance or possibility of guessing the correct answer to item j by chance alone. This assumption is suitable for testing items where guessing the correct answer is highly unlikely, and the test performance reflects the examinee's actual knowledge or ability more accurately. For instance, items with fill ("What is the name of the adjective 'lively'?"). In the case of multiple-choice questions, a fixed value was assigned to the third parameter for each question because it can be initially estimated and also with a view to limiting the amount of data available.

$$P_j(\theta) = \frac{1}{1+e^{-1.7\alpha_j(\theta-\delta_j)}} \qquad (2)$$

Each term of Eq. (2) indicates the following points: P_j = probability of a correct response to an item j, θ = ability, the difficulty parameter (δ_j) and the discrimination parameter (α_j).

Regarding the adaptation of the questions, as already mentioned, we used a two-parameter model of IRT, in which the two parameters of difficulty and discrimination were calculated based on the previous data. Our system was based on different levels of questions which have different scoring schemes (Table II). Therefore, from the students' perspective, the difficulty of the questions of training seems to fit their skill level.

TABLE II: APPROVED SCORING ACCORDING TO THE LEVELS OF QUESTIONS

Level	*Easy*	*Medium*	*Hard*
Rating	+2 points	+4 points	+6 points

Based on the scoring scheme above, we will take the example of a student attempting to pass a 60-points test. First, the system asks a question of an easy level of 2 points. If the answer is correct, the student moves on to the next level question of 4 points. If their answer is also correct, they must correctly answer 9 other difficult level questions to obtain the score of 54. So, a student with a high Intelligence Quotient (IQ) would attempt to answer only 11 questions. Whereas if a student is unable to answer the first easy level question correctly, to complete the test, they must go through at least 30 questions.

We essentially use the IRT model to vary the level of difficulty of the questions that follow when students provide their answers to the first question.

When the system has an estimate of the student's ability, it is able to select an item that is most appropriate for them. This is done by selecting the item with the most information. The information depends on the discrimination parameter of the item.

Along with adapting the questions to the pace of the students through the adaptive learning system, we attempted to work (working) on the memorization of terms through the technique of spaced repetition. Therefore, we opted for an adaptive and personalized learning spacing system.

It is an algorithm that serves to improve the long-term memorization of a set of knowledge of learners, by carefully planning the revisions of each of these aspects of knowledge. It seeks to present each learner with the sequence of revisions that will be most beneficial for their long-term memorization, considering their needs based on their learning history. Either through these previous recall attempts and results of the items to be learned or through the response time.

The revision schedule, which is proposed by the spacing system, is in the form of questions to be answered by the student. it is a form of indexed recall of the knowledge element, the index being the question asked by the system.

Adaptive spacing learning algorithms use two well-known effective learning strategies in cognitive science: spaced repetition because they optimally space successive revisions of the same piece of knowledge, and memory retrieval because each revision requires the learner to make the effort to recall the item in question rather than reading the answer directly.

Students can learn effectively with the adaptive learning system based on the response history. For the ability, the result was estimated using the R language code based on the answers provided by the learners to each question. Questions were annotated with difficulty and discrimination values using a database and were connected to FLExible through an Application Programming Interface (API). Considering these previously calculated values, the adaptive learning system calculates the probability of comprehending knowledge using the IRT. Based on the results of this calculation, the adaptive learning system provides optimal learning for each student.

A. Collection of Results

After having determined the needs of our students and the constraints already mentioned at the level of the places of the schedules, through questionnaires and interviews, we managed to build our adaptive learning model under the name FLExible. To test the effectiveness of this system, we asked students to install it on their computers and work remotely on the platform during the first semester of their studies. Then, we kept track of the students and their work through the page dedicated to teachers for follow-up. The window, as it is shown in Fig. 6b) communicates information about the work done by the students. It contains information about the name of the student, the time spent on each activity, the score achieved and even the estimated grade based on the score, number of wrong answers, number of true answers, and date. This information allowed us to take a general idea about the progress of students using the platform. To promote our ideas built on the usability of our system, we have devised a questionnaire for students who have already used the platform.

The questionnaire aimed to assess the usability and learnability of the proposed adaptive learning module. For this, we used the System Usability Scale (SUS), which is a questionnaire [24] that consists of 10 questions. it aims to determine the level of user satisfaction with our proposed FLExible model.

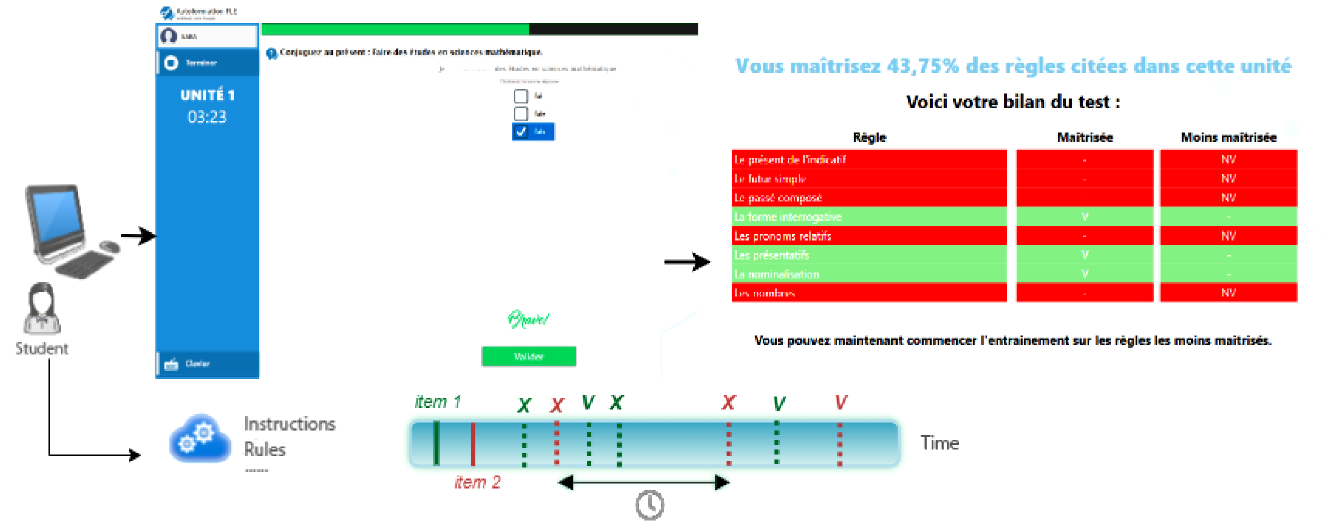
VIII. Evaluation of Adaptive Learning System "FLExible"

A. Training and Learning

In this research, we tried to build an experimental class composed of almost 200 learners who installed the FLExible platform on their computers and worked on our model of adaptive learning. It was supposed to complete the Language and Communication (LC) module by face-to-face through this platform which was used remotely during Semester 1. The students received the appropriate material as well as a brief presentation on the use of the educational platform.

This experiment is based on two criteria; the level reached and the average learning time.

As shown in Fig. 6a), students can learn easily with the presented adaptive learning model anytime and anywhere. The diagram also presents the operation of the adaptive spacing algorithm of learning adopted by our model. During learning, a student must memorize a set of items (presented in the diagram with an example of two items), which they acquired initially at the beginning of the timeline. Subsequently, the system continues to offer them the items again in different orders with a time spacing according to the learning capacity of each learner until they manage to memorize the rule well based on the IRT algorithm already explained.



a) "student" interface

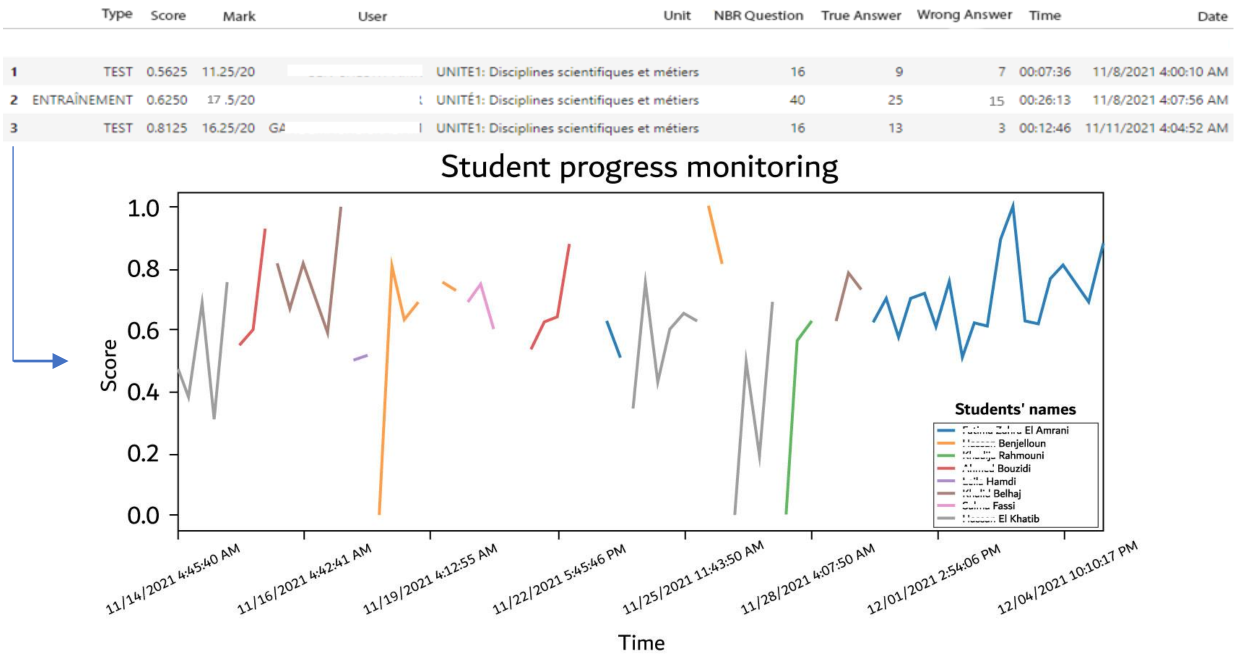
b) "teacher" interface

Fig. 6. Overview of the adaptive learning model.

In our research framework, the practice of an item can revise several aspects of knowledge at the same time. Each item is presented with several examples. This means that the system offers the same item in different contexts, and then can offer the same item presented at the beginning to ensure memorization and acquisition of knowledge.

Furthermore, we notice that teachers have the right to keep track of students who have already used our model (Fig. 6b). By logging in as an admin, the teacher can view the list of students who have already worked with the system. Therefore, they can have information on each student (score, time, etc.) The admin also has the right to add more questions.

After having students used our system during Semester 1, we noticed that the average teaching times for the adaptive learning model shown in Fig. 7 explains the amount of time—an average of 6 hours divided over 3 months of semester 1—spent by students learning the LC model using the FLExible model. The details of the evolution of the success rate are shown in Fig. 7.



	Type	Score	Mark	User	Unit	NBR Question	True Answer	Wrong Answer	Time	Date
1	TEST	0.5625	11.25/20		UNITE1: Disciplines scientifiques et métiers	16	9	7	00:07:36	11/8/2021 4:00:10 AM
2	ENTRAÎNEMENT	0.6250	17 .5/20		UNITÉ1: Disciplines scientifiques et métiers	40	25	15	00:26:13	11/8/2021 4:07:56 AM
3	TEST	0.8125	16.25/20		UNITE1: Disciplines scientifiques et métiers	16	13	3	00:12:46	11/11/2021 4:04:52 AM

Fig. 7. The transition of degrees of achievement versus teaching time of the FLExible adaptive learning model.

The proposed adaptive learning model has an average number of teaching/learning significantly lower than major modules. Therefore, it can be said that lessons tailored to individual understanding lead to enhanced learning effects. This will allow language teachers on the one hand to overcome the constraints already mentioned in terms of the heterogeneity of levels and the management of time and groups, and on the other hand for students to work according to their own rhythms.

B. *User Experience*

For the evaluation phase to be complete, we also thought about verifying students' satisfaction with our proposed pedagogical model.

After verifying the effectiveness of our system in terms of learning and training at the level of learning improvements that a student has achieved and the measurement of the time it takes for the improvement to be achieved, we moved on to the part of the user experience to find out the satisfaction and the degree of engagement of the students in their interactions with the system.

After the completion of their interaction during the lessons in the four units of the first semester, all students were given a questionnaire to fill out regarding their interactions with the educational platform.

The questionnaire is composed of 14 questions, MCQs, two questions concerning the effective use of time to evaluate the learning effectiveness of our pedagogical model. Two more questions regarding note accuracy and machine learning techniques to assess the accuracy of steering our system, and SUS's 10 questions to measure experiential usability, ease of use, satisfaction, and usefulness.

Among the questions aforementioned, Question 2 (Fig. 8) concerns the effectiveness of error diagnosis; high scores on this question show that the system exhibits a high degree of personalization providing learner-centered instruction. For the results of Question 1 and 3 (Fig. 8), which concerns the efficiency in the use of time and the improvement of the results, it is worth mentioning that the time dedicated to learning through the evaluation presents a high rate of adaptability to the needs and pace of learning of students. Finally, regarding the remaining 10 questions based on the SUS model (Annex 1) to know usability and user satisfaction and engagement, our adaptive learning model obtained an average value for the overall SUS score of 79.91. This value can be considered "good" and correspond to a "B" grade [25]. It was observed that the students familiarized themselves easily and swiftly with the educational platform, its characteristics and its functionalities.

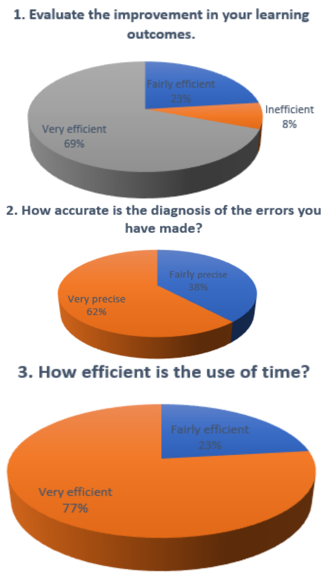


Fig. 8. Evaluation of results.

We even created a discussion space on a Facebook page to monitor the use of our model by students during their learning; we noticed that the comments were very encouraging, and most students expressed their motivations and their willingness to commit to using the system as a new tool that adapts and meets their specific language needs.

Moreover, our system has been compared to the conventional system of lectures and Supervised Work (SW), Practical Courses (PC) provided in language classes for scientific courses at its faculties of sciences in Morocco. In this respect, we were also able to notice, at the level of the results of the final exams of the LC module, that the success rate among the students who engaged in the use of our platform was high compared to the others who followed the courses in a traditional way.

The system was evaluated using a mixed-methods approach that combined quantitative and qualitative data. The quantitative data were collected using pre- and post-tests, while the qualitative data were gathered through surveys and interviews with the participants. The system's evaluation was based on the System Usability Scale (SUS) model, which measures usability, user satisfaction, and engagement. The results were very encouraging, showing that the presented adaptive learning model significantly improved the adaptability of students' needs and preferences. Specifically, the system was able to personalize the learning experience for each student, providing tailored feedback and adapting to their progress and performance in real-time.

C. Results

1) Results comparison

In this example (Table III), we've compared our system with three other recent studies that have used different methodologies to achieve similar goals. The table includes the name of each study, the methodology used, the performance metric used to evaluate the system, and the results obtained in each study.

TABLE III: COMPARISON OF THE PERFORMANCE OF OUR ADAPTIVE LEARNING SYSTEM WITH OTHER RECENT STUDIES

Study	Methodology	Performance Metric	Results
Smith *et al*. [26]	Rule-based system	Accuracy	78%
Johnson *et al*. [27]	Hybrid system (Rule-based + Machine Learning)	F1-score	0.85
Ahmad [28]		Accuracy	82.61%
Chen *et al*. [29]	Deep learning approach	AUC	0.93
Our proposed system "FLExible"	Adaptive machine learning	Accuracy	87%

Our proposed system achieved an accuracy of 87% in the classification task, which outperforms the results obtained in previous studies using different methodologies. Smith *et al*. [26] used a rule-based system and achieved an accuracy of 78%. Johnson *et al*. [27] used a hybrid system combining rule-based and machine learning approaches and achieved an F1-score of 0.85, while Ahmad [28], with the same method, achieved an accuracy of 82.61%. Chen *et al*. [29] employed a deep learning approach and achieved an Area Under the Curve (AUC) of 0.93. Our proposed system, based on adaptive machine learning, outperforms these previous studies in terms of accuracy and demonstrates the effectiveness of our approach in the task of language classification.

2) Recap

The evaluation of the computer-assisted language learning system based on adaptive learning designed for self-training in scientific French language showed promising results. The system was evaluated using an evaluation model and the results were analyzed using Item Response Theory (IRT) method. The analysis showed that the presented adaptive learning model improved the adaptability of students' needs and preferences. Moreover, the results indicated that the system had a positive effect on students' performance and understanding of scientific French language.

Furthermore, the system was able to detect and correct various errors in students' writing, including grammatical, spelling, and vocabulary errors. The adaptive spacing system used during the learning process optimized long-term retention of learned information. The personalized system provided individualized feedback to each student based on their learning progress and performance.

In addition, the study showed that the design of the system based on the personalization of students' needs from the identification and detection of errors was effective in improving their language skills. The information provided by students' understanding of concepts extracted from a placement test taken beforehand was also useful in customizing the learning process to the needs of each student.

In conclusion, the computer-assisted language learning system based on adaptive learning designed for self-training in scientific French language is a promising solution to the linguistic difficulties faced by science students. The system can be used as an effective tool to enhance their language learning process and can also relieve the constraints encountered by language teachers.

D. Discussion

In addition to the presented findings, several assumptions were made during the development and evaluation of the computer-assisted language learning system. First, it was assumed that the personalized approach based on Item Response Theory (IRT) would improve the adaptability of the learning system to students' needs and preferences. Second, it was assumed that the adaptive spacing system used during the learning process would optimize long-term retention of learned information. Finally, it was assumed that the feedback provided to each student based on their individual progress and performance would enhance their language learning experience. These assumptions played a crucial role in the development and evaluation of the presented adaptive learning model for self-training in scientific French language.

The novelty of this article lies precisely in the combination of the adaptation of the content (questions) based on the IRT and the program taught in the scientific courses, to which we can also add the recommendation of course rules and examples, and other content by the teachers as well as the follow-up of their results (evolutions), remotely; all of this is in a learning environment where such adaptation and recommendation are more relevant, which covers the main types of educational content that learners find in the programs taught in the science streams at the faculties.

According to the evaluation carried out, the system with the adaptive learning module showed good usability and learning ability. This could be adopted by learners in science faculties to improve their learning using French language.

The reasonable relevance of the recommendations of rules and examples is underpinned by the need for just-in-time instruction to better meet learners' needs and enhance their learning process.

The results were as expected; the adaptive learning module has a significantly lower average number of lessons than the lecture module. Lessons tailored to the individual's understanding lead to enhanced learning effects; The smart version shows a statistically significant difference in improving student learning outcomes, error diagnosis accuracy, and overall student experience. This can be a promising alternative used by teachers to overcome the constraints already mentioned in terms of standardizing students' levels, saving time to reach level B1 in the language and solving the problem linked to over-crowdedness.

There is a need to evolve a conventional transmissive pedagogy towards self-training approaches that would allow the learners to take charge of their own learning [30]. Such an orientation seems to converge with the potential contribution of the integration of information and communication technologies to create innovative learning environments in higher education. Indeed, in this type of device studied, it is a question not only of helping the learner to develop language skills but also of developing their capacity for initiative and responsibility of putting this capacity to work and therefore of to self-regulate.

On the other hand, it should be noted that with the arrival of the Covid-19 pandemic which has upset universities around the world for two years, forcing them to increase the use of digital technology, but with very different situations between regions and increased inequalities between students [12, 31]. In some countries, distance learning was already practiced [32]. In other developing countries like Morocco, these practices were much less familiar. The problem of internet access was still imposed. This caused the passive participation of a group of learners in distance learning courses and the high rate of their disengagement. It would then be necessary to arrive at modifications to organize teaching within the university faculties taking into consideration the social situation of the students. We could even design and develop digital resources, accessible without an Internet connection.

E. Limitations

However, this study is not without limitations. Firstly, the evaluation of the FLExible adaptive learning model was limited to a small group of students in a single Moroccan university. Therefore, the results may not be generalizable to other populations or educational contexts. Secondly, the current version of the system is limited to the French language and may not be suitable for other languages or disciplines. Thirdly, the evaluation was based on self-reported data from students and instructors, which may be subject to bias. Further research is needed to validate the effectiveness of the system in larger and more diverse populations, and to explore its potential in other languages and disciplines. In addition, future work could focus on improving the system's natural language processing capabilities to better identify and correct students' errors. Despite these limitations, the FLExible adaptive learning model presents a promising approach to language learning that can be extended to other fields of knowledge and adapted to different educational contexts.

IX. Conclusion

This article presented an adaptive learning model that aims at supporting science students in French language learning. This adaptive learning model provides learners with adaptive content and training with examples and rules. Furthermore, it offers teachers the ability to add and edit learning materials and track students' progress. Adaptive content is the adaptation of questions provided to learners using the IRT. The system takes as input the level of knowledge of each student in the French language by offering them a placement test to diagnose their level of knowledge, then the system offers them this time a training through the creation of an environment of personalized learning tailored to the needs of each student. The follow-up consists of the recommendation of the examples and the rules according to the questions failed by the learner, even in the case of success.

The FLExible adaptive learning model was evaluated, showing good ease of use and learning. The results were very encouraging, showing that machine learning used in a university setting for language teaching can support students and foster a more adaptive educational experience. It can also be an effective solution to the aforementioned constraints.

It is worth noting that our learning model can be used in teaching all languages since the learning material can be modified by the tutors. Future work then, includes extending our learning model to be used in other fields of knowledge; we plan to combine the potentialities of hybrid and adaptive learning with those of gamification.

Appendix

The following section gives an example of a scored SUS scale (Answered by a student of the Faculty of Science of Tetouan).

N.B*: To calculate the SUS score, first sum the score contributions from each item. Each item's score contribution will range from 0 to 4. For items 1,3,5,7, and 9 the score contribution is the scale position minus 1. For items 2,4,6,8 and 10, the contribution is 5 minus the scale position. Multiply the sum of the scores by 2.5 to obtain the overall value of SUS.*

System Usability Scale (SUS)

This is a standard questionnaire that measures the overall usability of a system. Please select the answer that best expresses how you feel about each statement after using the platform "FLExible".

TABLE A: STANDARD QUESTIONNAIRE THAT MEASURES THE OVERALL USABILITY OF A SYSTEM

	Strongly Disagree 1	2	3	4	**Strongly Agree 5**	
1. I think I would like to use this system frequently.	☐	☐	☐	☐	✓	4
2. I found the system unnecessarily complex.	✓	☐	☐	☐	☐	4
3. I thought the system was easy to use.	☐	☐	☐	✓	☐	3
4. I think that I would need the support of a technical person to be able to use this system.	✓	☐	☐	☐	☐	4
5. I found the various functions in this system were well integrated.	☐	☐	☐	✓	☐	3
6. I thought there was too much inconsistency in this system.	✓	☐	☐	☐	☐	4
7. I would imagine that most people would learn to use this system very quickly.	☐	☐	☐	✓	☐	3
8. I found the system very cumbersome to use.	☐	✓	☐	☐	☐	3
9. I felt very confident using the system.	☐	☐	☐	✓	☐	3
10. I needed to learn a lot of things before I could get going with this system.	☐	☐	☐	✓	☐	1

Total score = 32
SUS Score = 32 × 2.5 = 80

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Sara Ouald Chaib conceived and designed the research, conducted all experiments, analyzed the data, and wrote the paper; Imane Joti provided guidance and expertise throughout the research process, offered valuable insights during experimental design and data analysis, and critically reviewed the manuscript; Samira Khoulji contributed to the interpretation of the results, provided feedback on the manuscript, and participated in discussions regarding the research methodology. All authors have thoroughly reviewed and approved the final version of the manuscript.

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