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# ChatGPT as an Intelligent Self-Continuous Professional Development Tool for Teachers IMMS – ARCS

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**Abstract** Artificial intelligence, with its vast capabilities, has permeated various sectors of society, including education. This technological revolution has brought significant changes to both teaching and learning processes. This study aims to assess teachers' motivation to utilize AI-based tools, specifically ChatGPT, as a means of self-professional development to aid in the preparation of their pedagogical tasks. To this end, an online training session on the use of ChatGPT-4 was conducted with 41 physics teachers in the Fez-Meknes region of Morocco. During this training, teachers prepared lessons using both traditional and AI-enhanced methods. To measure their motivation towards the intelligent method, the IMMS-ARCS survey -based on four factors (Attention, Relevance, Confidence, and Satisfaction)- was employed, a global Alpha Cronbach=0.901 indicates an excellent internal consistency between the 36 items. The results indicate that teachers generally exhibit a positive attitude towards using ChatGPT as an innovative tool that can assist and streamline their teaching tasks. Additionally, the findings reveal that the four motivational factors are positively correlated, with higher values of these predictors indicating greater overall teachers' motivation to adopt ChatGPT-4 as an intelligent tool for self-development of new skills to improve their competencies, ultimately, enhancing students' outcomes.

**Keywords** Artificial Intelligence, Continuous Professional Development, Moroccan in-service Teachers, IMMS, Online Training, ChatGPT

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## 1. Introduction

The integration of artificial intelligence (AI) in educational practices represents a transformative shift in how teaching and learning are approached [1]. AI technologies offer innovative solutions to support and enhance teachers' professional practices [2], providing tools that can analyze student data [3], personalize learning experiences [4], and automate administrative tasks [5]. These advancements enable teachers to focus more on instruction and student engagement, potentially leading to improved educational outcomes.

However, the adoption of AI in the educational sector also presents challenges, including the need for professional development [6], the requirement for robust technological infrastructure, and concerns over data privacy [7]. As educators navigate these complexities, understanding their attitudes and readiness to embrace AI is crucial for successful implementation [8]. By leveraging AI effectively, teachers can create more adaptive, efficient, and personalized learning environments that cater to the diverse needs of their students.

This paper is motivated by the growing importance of integrating Artificial Intelligence (AI) in education, particularly in enhancing teachers' professional development. The primary contribution of this study is the

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empirical assessment of teachers' motivation to adopt AI-based tools, as part of their Continuous Professional Development. By employing a robust methodological approach, this research provides valuable insights into the factors that influence teachers' willingness to embrace AI in their instructional practices. Furthermore, the study offers practical recommendations for teacher training programs and educational policies, contributing to the broader discourse on effective AI integration in education.

The ultimate goal is to demonstrate how the utilization of CHATGPT-4 can lead to significant improvements in educational practices and student outcomes, thereby contributing to the broader discourse on educational innovation and teacher professional development.

This study is part of ongoing research efforts [8, 9], aimed at addressing the issue of Moroccan teachers abandoning CPD training programs due to traditional methods employed by policymakers [10]. It seeks to revitalize these CPD programs and give them a new lease on life.

The findings of this study indicate that participant teachers exhibit positive attitudes towards the use of AI-based tools, especially in terms of satisfaction and confidence. This is a promising indicator for the adoption of such technologies as an intelligent self-CPD tool for teachers.

## 2. Literature review

### *2.1. AI technologies.*

*2.1.1.* ***Generative AI:*** Generative Artificial Intelligence (AI) is a groundbreaking area within AI technology that focuses on generating new, original content or data that resembles human-created outputs. This technology leverages sophisticated algorithms and neural network structures [11], including:

- **Generative Adversarial Networks (GANs)**: These involve two networks, the generator and the discriminator, which are trained concurrently. The generator produces data intended to appear genuine, while the discriminator assesses whether the data is real or generated. This rivalry compels the generator to create increasingly realistic data [12].
- **Variational Autoencoders (VAEs)**: VAEs work by encoding data into a compressed form and then decoding it back into the original data. They excel at generating complex data by learning the probability distribution of the data's features [13].

*2.1.2.* ***Machine learning:*** Machine learning, a branch of artificial intelligence, centers on creating algorithms and statistical models that allow computers to learn from data and make predictions or decisions [14]. Instead of being explicitly programmed to perform a task, these systems improve their performance by recognizing patterns and making data-driven inferences [15].

This approach encompasses various techniques, such as supervised learning, where the model is trained on labeled data; unsupervised learning, which involves finding hidden patterns in unlabeled data; and reinforcement learning, where an agent learns to make decisions by receiving rewards or penalties [16]. Machine learning has become integral to numerous applications, including image and speech recognition, recommendation systems, and predictive analytics, driving advancements across diverse fields.

*2.1.3.* ***Deep Learning:*** Deep learning, a branch of machine learning, has transformed data interpretation, achieving remarkable progress in understanding complex large datasets. This computational technique, based on neural networks with multiple layers, has developed from early artificial neuron concepts to advanced architectures that can surpass human performance in certain tasks [17]. The pioneering research by Hinton, LeCun, and Bengio in the early 2000s established the groundwork for deep learning, showcasing its ability to learn data representations without explicit programming.

Deep learning applications have since spread across various domains, achieving notable success in image recognition, where deep convolutional neural networks (CNNs) have become the benchmark for tasks like object detection and classification [18]. In natural language processing (NLP), deep learning methods such as recurrent

neural networks (RNNs) and transformers have revolutionized language translation, sentiment analysis, and text generation, demonstrating a high capability to comprehend and generate human language accurately.

*2.1.4.* ***Natural Language Processing (NLP):*** Natural Language Processing (NLP) acts as the intermediary between human communication and computer comprehension, enabling the automated analysis and creation of natural languages. This discipline employs computational methods to interpret the complexities of human language, striving to enhance human-machine interaction [19].

NLP encompasses a wide range of applications, such as speech recognition, sentiment analysis, machine translation, chatbots, and text summarization. These applications are revolutionizing industries by offering more intuitive user interfaces, automating customer service, and enabling real-time cross-lingual communication [20].

### *2.2. ChatGPT in education*

ChatGPT, a product of OpenAI , is a language model based on the Generative Pre-trained Transformer (GPT) architecture. Since its introduction, ChatGPT has seen widespread application in various domains, including customer service, education, and creative writing. Its capabilities to generate coherent and contextually relevant text have made it a subject of extensive research [21].

The integration of ChatGPT into educational field is gaining traction. The model's ability to provide instant feedback, generate content, and assist in language learning makes it a valuable tool for educators and students [22, 23]. ChatGPT can adapt to individual learning styles, providing personalized responses and feedback [24]. This adaptability is crucial in addressing the diverse needs of learners leading into bridging the gap between different learning paces and styles [25, 26, 27].

Moreover, the model can act as a 24/7 virtual tutor, offering explanations and answering questions across various subjects [28]. This capability is particularly beneficial in remote learning environments where learners may lack immediate access to online support [29].

Additionally, ChatGPT's proficiency in natural language generation makes it an excellent tool for language practice, helping learners improve their conversational skills. Language learning involves not only the acquisition of vocabulary and grammar but also the ability to use language fluently and contextually [30, 31].

### *2.3. Research context*

Teachers' acceptance of AI-based tools in practical professional situations is a crucial determinant of the successful integration of these technologies to enhance student outcomes [32]. Recent studies indicate that teachers' acceptance is influenced by multiple factors, including perceived usefulness, ease of use, and the alignment of AI tools with pedagogical goals [33, 34]. When AI-based tools are perceived as user-friendly and directly beneficial in improving instructional practices and student learning, teachers are more likely to embrace them [35].

Additionally, professional development that includes hands-on training and continuous support fosters a positive attitude towards these technologies; In this context, Fakhar et al. underscore the necessity of developing an effective strategy for integrating AI into professional vocational training programs. Teachers have highlighted the critical need for sufficient training and support to effectively utilize AI-based tools, thereby ensuring the successful incorporation of AI into their teaching practices. [9].

Moreover, the alignment of AI tools with curriculum standards and their ability to provide personalized learning experiences further enhances teachers' willingness to integrate them into their teaching [36]. As a result, AI-based tools can significantly improve student engagement [37], tailor educational experiences to individual needs [38, 39], and provide real-time feedback [40], thereby fostering better student outcomes. In this context:

- How do Moroccan teachers perceive and accept the integration of AI-based tools, especially ChatGPT, in their professional practice?
- And what are the specific opportunities they harness from utilizing these technologies to enhance Moroccan students' outcomes?

These questions aim to explore both the attitudes of teachers towards AI tools and the unique contextual factors in Morocco that might influence their adoption and effectiveness.

## 3. Methodology

### *3.1. Study Design*

To gain a thorough understanding of the factors influencing teachers' motivation toward AI-based tools, as well as their practical impact on teaching efficacy and student engagement, we conducted an experimental comparative study, focusing on two groups of physics teachers. Each group is tasked with preparing a lesson presentation on a topic of their choice, employing two distinct methods. notably:

- **Traditional method**: Preparing a N diapositives PowerPoint presentation of a lesson using traditional tools (search engines, books, websites, designing the presentation manually using Microsoft office PowerPoint).
- **Intelligent method**: Preparing a N diapositives PowerPoint presentation of a lesson of a different topic using the intelligent tool ChatGPT. They can also use other intelligent tools like the designers of PowerPoint presentations, Auto generators of Images, sounds, simulation and videos).

This approach allows us to systematically compare the efficacy of ChatGPT and other AI-based tools versus traditional methods in lesson preparation. By analyzing the differences in the quality of the presentations, the time spent on preparation, and the overall satisfaction and motivation of teachers.

### *3.2. Study process*

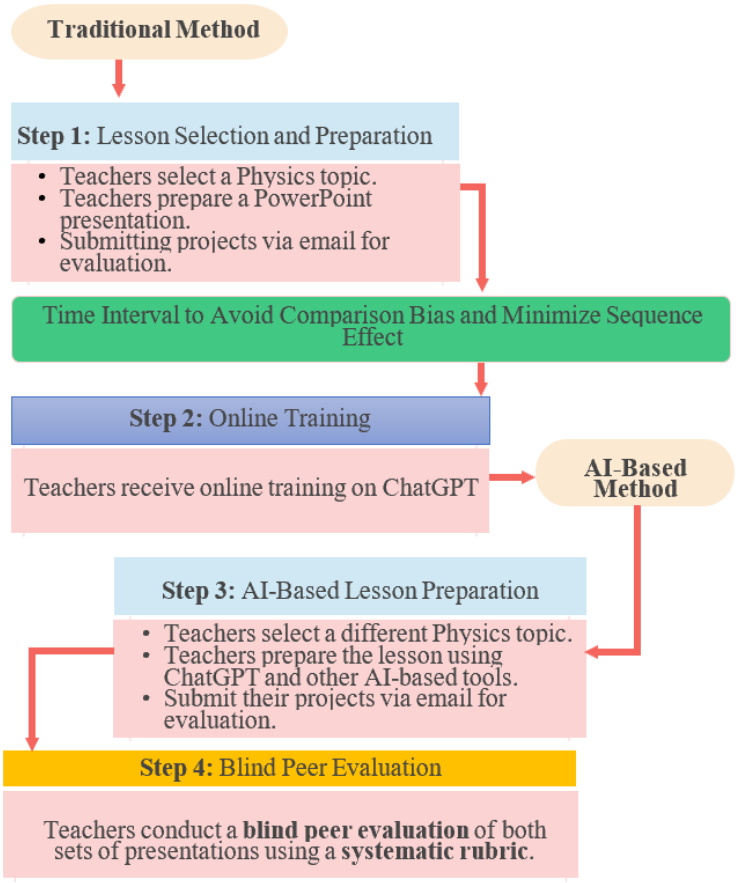


Figure 1. Study process overview.

**Firstly**, the teachers were asked to select and prepare a PowerPoint presentation on one of the suggested topics within their teaching subject (*see list of topics in appendix B*). They then submitted these projects via email for evaluation. To avoid comparison bias and minimize sequence effects, we provided a sufficient time interval between tasks.
**Secondly**, we conducted an online training session for the teachers, focusing on the utilization of AI-based tools in lesson preparation and especially the generative AI ChatGPT. Following this training, the teachers were instructed to choose a different lesson topic from their initial presentation and prepare it using the newly acquired AI-based methods.
**Finally**, we implemented a **blind peer evaluation process** where every teacher was asked to evaluate randomly a project of one of other teachers using a systematic rubric, comparing the presentations prepared with traditional methods to those prepared with AI-based tools. This peer evaluation aimed to assess the effectiveness, quality, and overall impact of the two different preparation methods. Figure 1 represents the process of the two methods.

### *3.3. Training procedure*

The training was conducted entirely online using the Moodle LMS, where participants accessed tutorials we prepared on how to harness the benefits of ChatGPT-4. They also participated in daily 2-hour synchronous sessions over the course of a week, allowing them to discuss directly with the trainers any challenges or constraints they encountered in course preparation using ChatGPT.

### *3.4. The sample*

The sample of this experimental study is chosen based on some pre-identified criteria, notably: Teachers of sciences Physics.

- High School teachers.
- Teachers who never utilized AI in their professional life.
- Teachers who are working in Fez-Meknes Academy, especially in Fez and Moulay YAKOUB provincial directorates.
- No age, working years, or gender restrictions.

After sharing our training information on social media (Facebook, Instagram, WhatsApp), 53 teachers expressed their desire to participate, but after contacting them, there were only **41 teachers** who never used ChatGPT, Hence, we selected 41 teachers to participate in our experience as detailed in Table 1 below

Table 1. Demographic Information of Participants.

| | | | |
|---|---|---|---|
| **Gender** | Male | 22 | **53,7%** |
| | Female | 19 | **46,3%** |
| **Subject** | Physics | | |
| **Age** | 20 – 30 | 3 | **07,32%** |
| | 31- 40 | 25 | **60,97%** |
| | 41-50 | 13 | **31,71%** |
| **Teaching Years** | 5-10 years | 18 | **43,90%** |
| | 10-15 years | 13 | **31,71%** |
| | 15- 20 years | 10 | **24,39%** |

### *3.5. Study's data*

*3.5.1. Projects evaluation :* The evaluation of projects is conducted using the Blind Peer evaluation method, wherein each teacher is randomly assigned to anonymously assess the project of another teacher. This evaluation is based on a set of criteria developed by Rakibi et al [41], in collaboration with experts. These criteria include the formulation of the presentation objectives, the content of the presentation, as well as the pedagogical aspects and visual media used. (*For more details see appendix A*).

*Why Peer evaluation?* Peer evaluation among teachers has proven to be an effective method for professional

development, fostering a collaborative learning environment that enhances teaching practices [42]. Studies indicate that peer evaluation promotes reflective practice, as teachers receive constructive feedback from colleagues who understand the intricacies of the classroom setting [43]. This process encourages self-regulation, and a shared commitment to improving instructional strategies [44]. Furthermore, peer evaluation helps build a supportive community of practice [45], where teachers feel empowered to be an active part of the training.

*3.5.2. Data Collection : Why IMMS?* The Instructional Materials Motivation Survey (IMMS) was utilized in this study due to its established validity and reliability in assessing users' motivation. Developed by John M. Keller [46]. Its robust psychometric properties have been confirmed through extensive empirical research, making it a widely recognized and credible tool for evaluating motivational aspects in various educational contexts. The use of the IMMS ensures that the data collected is both accurate and meaningful, thereby enhancing the overall rigor and trustworthiness of the study's findings.

As illustrated in Figure 2 below, the IMMS is grounded in the ARCS model of motivation, which encompasses Attention, Relevance, Confidence, and Satisfaction.

- **Attention**: This dimension measures how well the instructional materials capture and maintain the learners' interest. It includes elements like the use of novel, surprising, or varied presentation styles to keep learners engaged.
- **Relevance**: This dimension assesses how well the instructional materials relate to the learners' personal goals, needs, and interests. It includes elements like goal orientation, matching content to learners' experiences, and highlighting the utility of the content.
- **Confidence**: This dimension evaluates how the instructional materials help learners believe in their ability to succeed. It includes elements like providing clear objectives, scaffolding learning experiences, and giving constructive feedback.
- **Satisfaction**: This dimension assesses the degree to which learners experience a sense of reward or achievement from engaging with the instructional materials. It includes elements like intrinsic and extrinsic rewards, and opportunities for applying what they've learned.


Figure 2. ARCS model's path.

*3.5.3. Data analysis :* To address the research objectives, a conceptual framework has been developed featuring four (04) independent variables and one dependent variable. This framework is illustrated in Figure 3.

**-One dependent variable:**

- Motivation=MEAN(all 36 items).

**-Four independent variables:**

- Confidence= MEAN(9 items of Confidence factor).
- Attention=MEAN(12 items of Attention factor).
- Satisfaction=MEAN(6 items of Satisfaction factor).
- Relevance= MEAN(9 items of Relevance factor).

To achieve our study's goal, the following hypotheses are being considered:

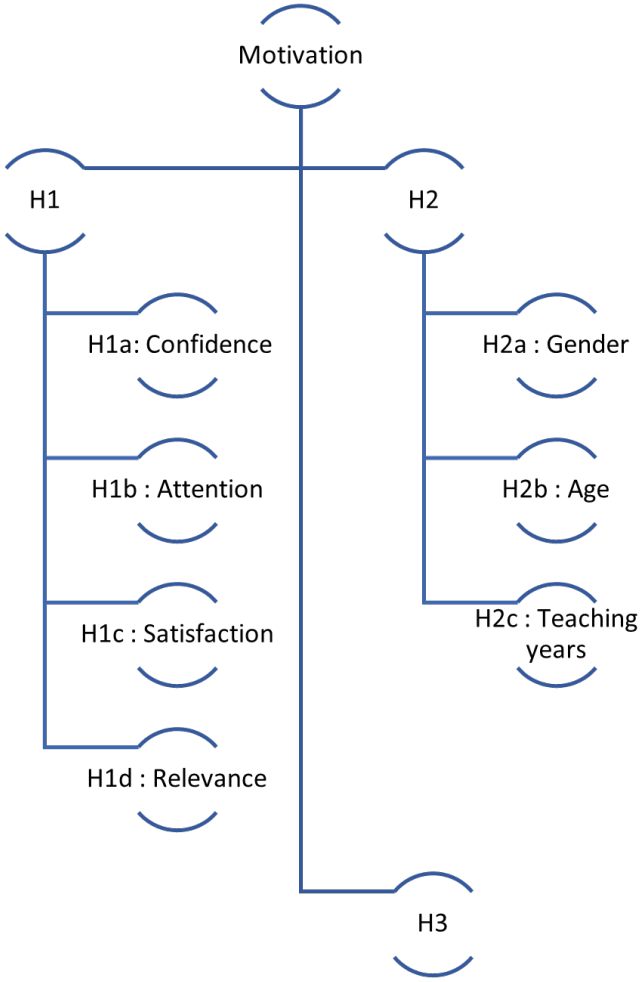


Figure 3. Conceptual framework illustration.

- **H1**: The four independent variables are positively correlated with teachers' motivation towards ChatGPT-4.
- **H2**: The demographic variables positively impact teachers' motivation towards ChatGPT-4.
- **H3**: The use of ChatGPT improves the quality of courses prepared by teachers.

Using the statistical software tools JAMOVI and MS Excel, we employed a combination of qualitative descriptive analysis and quantitative statistical methods to comprehensively evaluate the factors influencing teachers' motivation toward AI-based tools, specifically ChatGPT-4, in their professional development. The primary statistical techniques included multi-linear regression analysis, which was used to examine the relationship between the independent variables—Attention, Relevance, Confidence, and Satisfaction (as measured by the IMMS survey)—and the dependent variable, teacher motivation. This approach allowed us to quantify the impact of each motivational factor on overall teacher motivation.

To ensure the robustness of our findings, we conducted reliability tests for the IMMS survey, with Cronbach's alpha and McDonald's omega being calculated to assess the internal consistency of the scale. Additionally, Pearson correlation analysis was employed to explore the relationships between the various motivational factors, revealing significant positive correlations that further informed our regression model.

We also investigated the relationship between teachers' motivation and their demographic variables, such as gender, age, and years of teaching experience. Independent samples t-tests were conducted to compare motivation levels across different gender groups, while one-way ANOVA tests were used to analyze variations in motivation across different age groups and levels of teaching experience. These analyses allowed us to determine whether demographic factors significantly influenced teachers' motivation to adopt AI-based tools in their professional development.

Finally, paired samples t-tests were performed to compare the effectiveness of traditional and AI-enhanced methods in lesson preparation. This test provided insights into the differences in teachers' perceptions and experiences with each method, offering a statistical basis for our conclusions.

## 4. Results

### *4.1. Instrument reliability*

The Table 2 below, presents the reliability statistics for the IMMS dimensions, including Confidence, Attention, Satisfaction, Relevance, and the overall Global scale. The means, standard deviations, Cronbach's $\alpha$, and McDonald's $\omega$ values are reported for each scale.

Table 2. Scale Reliability Statistics.

| Dimensions | Mean | SD | Cronbach's α | McDonald's ω |
|---|---|---|---|---|
| **IMMS Confidence** | 3.76 | 0.553 | 0.692 | 0.700 |
| **IMMS Attention** | 3.71 | 0.520 | 0.753 | 0.768 |
| **IMMS Satisfaction** | 3.82 | 0.809 | 0.881 | 0.892 |
| **IMMS Relevance** | 3.69 | 0.667 | 0.818 | 0.823 |
| **IMMS Global** | 3.73 | 0.484 | 0.901 | 0.911 |

- The IMMS Confidence scale has $\alpha$ of 0.692, and $\omega$ of 0.700, indicating moderate reliability.
- The IMMS Attention scale shows a $\alpha$ of 0.753, and $\omega$ of 0.768, reflecting good reliability.
- The IMMS Satisfaction scale has high reliability, as evidenced by $\alpha$ of 0.881 and $\omega$ of 0.892.
- The IMMS Relevance scale has a $\alpha$ of 0.818, and $\omega$ of 0.823, indicating good reliability.
- The overall IMMS Global scale shows excellent reliability with a $\alpha$ of 0.901, and $\omega$ of 0.911.

### *4.2. Frequency analysis*

The following frequency Table 3 presents the distribution of responses for our key variables. This table provides an overview of how frequently each response category was selected by participants, allowing us to identify patterns and trends in the collected data.

Table 3. Participants' answers details.

| Items | | Mean | SD |
|---|---|---|---|
| **Confidence (9 items)** | | | |
| C1 | When I first used CHATGPT-4, I had the impression that it would be easy for me. | 3,51 | 1,165 |
| C2 | CHATGPT-4 was more difficult to understand than I would like for it to be. (-) | 4.27 | 0.949 |
| C3 | After consulting the introductory information, I felt confident that I understood what I was expected to learn from CHATGPT-4. | 3.34 | 0.855 |
| C4 | CHATGPT-4 had so much information that it was hard to pick out and remember the important points. (-) | 3.80 | 1.005 |
| C5 | As I worked on CHATGPT-4, I was confident that I could learn the content. | 3.76 | 0.994 |
| C6 | The activities provided by CHATGPT-4 were too difficult. (-) | 4.05 | 1.048 |
| C7 | After working on CHATGPT-4 for a while, I was confident that I would be able to pass a test on provided content. | 3.12 | 1.005 |
| C8 | I could not really understand quite a bit of the information in CHATGPT-4. (-) | 4.24 | 0.994 |
| C9 | The well-organized content helped me feel confident that I would learn effectively with CHATGPT-4. | 3.71 | 1.209 |
| | **Total Mean & SD** | **3.76** | **0.553** |
| **Attention (12 items)** | | | |
| A1 | There was something interesting in CHATGPT-4 that got my attention. | 3.83 | 1.093 |
| A2 | CHATGPT-4 is eye-catching. | 3.59 | 0.774 |
| A3 | The quality of the writing in CHATGPT-4 helped to hold my attention. | 3.73 | 0.837 |
| A4 | Information provided by CHATGPT-4 are so abstract that it was hard to keep my attention on it. (-) | 3.98 | 1.012 |
| A5 | The content provided by CHATGPT-4 look dry and unappealing. (-) | 3.83 | 1.093 |
| A6 | The organization of information in ChatGPT-4 effectively captured and maintained my attention | 3.44 | 0.896 |
| A7 | CHATGPT-4 has things that stimulated my curiosity. | 3.88 | 0.980 |
| A8 | The amount of repetition in CHATGPT-4 caused me to get bored sometimes. (-) | 3.12 | 1.229 |
| A9 | I learned some things with CHATGPT-4 that were surprising or unexpected. | 3.88 | 0.927 |
| A10 | The variety of reading passages, exercises, illustrations, etc., helped keep my attention on CHATGPT-4. | 3.73 | 1.001 |
| A11 | The style of writing in CHATGPT-4 is boring. (-) | 3.95 | 1.139 |
| A12 | There are so many words on each suggested content in CHATGPT-4 that it is irritating. (-) | 3.51 | 0.952 |
| | **Total Mean & SD** | **3.71** | **0.520** |
| **Satisfaction (6 items)** | | | |
| S1 | Completing the activities provided by CHATGPT-4 gave me a satisfying feeling of accomplishment. | 3.56 | 1.026 |
| S2 | I enjoyed CHATGPT-4 so much that I would like to know more about this technology. | 4.05 | 0.835 |
| S3 | I really enjoyed studying in CHATGPT-4. | 4.10 | 0.800 |
| S4 | The wording of feedback after the activities, or of other comments in CHATGPT-4, helped me feel rewarded for my effort. | 3.83 | 0.771 |
| S5 | It felt good to successfully complete content provided by CHATGPT-4. | 3.66 | 1.257 |
| S6 | It was a pleasure to work on such a well-designed program as CHATGPT-4. | 3.73 | 1.304 |
| | **Total Mean & SD** | **3.82** | **0.809** |
| **Relevance (9 items)** | | | |
| R1 | The content provided by ChatGPT-4 is clearly related to things I already know. | 3.56 | 1.001 |
| R2 | Stories, images, or examples were provided that demonstrated how ChatGPT-4 could be valuable for my students. | 3.44 | 1.305 |
| R3 | It was important to me to use ChatGPT-4 successfully. | 3.56 | 1.226 |
| R4 | Content provided by CHATGPT-4 is relevant to my interests. | 3.68 | 0.960 |
| R5 | There are explanations or examples of how people use the content provided by CHATGPT-4. | 3.27 | 1.025 |
| R6 | The content and style of writing in CHATGPT-4 convey the impression that it worth using. | 3.71 | 0.873 |
| R7 | The content provided by CHATGPT-4 was not relevant to my needs because I was already familiar with most of it. | 3.71 | 1.146 |
| R8 | I could relate the content of CHATGPT-4 to things I have seen, done, or thought about in my own life. | 3.78 | 0.962 |
| R9 | The content of CHATGPT-4 will be useful to me. | 4.46 | 0.809 |
| | **Total Mean & SD** | **3.69** | **0.667** |
| | **IMMS Global Mean & SD** | **3.73** | **0.484** |

### *4.3. Correlation inter-Factors*

Table 4. Correlation Matrix.

| | | Confidence | | Attention | | Satisfaction | | Relevance |
|---|---|---|---|---|---|---|---|---|
| **Confidence** | Pearson's r | — | | | | | | |
| | df | — | | | | | | |
| | p-value | — | | | | | | |
| **Attention** | Pearson's r | 0.847 | *** | — | | | | |
| | df | 39 | | — | | | | |
| | p-value | < .001 | | — | | | | |
| **Satisfaction** | Pearson's r | 0.355 | * | 0.411 | ** | — | | |
| | df | 39 | | 39 | | — | | |
| | p-value | 0.023 | | 0.008 | | — | | |
| **Relevance** | Pearson's r | 0.358 | * | 0.458 | ** | 0.826 | *** | — |
| | df | 39 | | 39 | | 39 | | — |
| | p-value | 0.021 | | 0.003 | | < .001 | | — |

Note. * p < .05, ** p < .01, *** p < .001

The analysis reveals that Confidence and Attention have a strong positive correlation ($r = 0.847$, $p < 0.001$), indicating that higher confidence is strongly associated with higher attention. Confidence is moderately correlated with both Satisfaction ($r = 0.355$, $p < 0.05$) and Relevance ($r = 0.358$, $p < 0.05$), suggesting that increased confidence is associated with higher satisfaction and perceived relevance. Attention shows a moderate positive correlation with Satisfaction ($r = 0.411$, $p < 0.01$) and Relevance ($r = 0.458$, $p < 0.01$), indicating that higher attention is associated with higher satisfaction and perceived relevance. Finally, Satisfaction and Relevance exhibit a strong positive correlation ($r = 0.826$, $p < 0.001$), suggesting that higher satisfaction is strongly associated with higher perceived relevance.

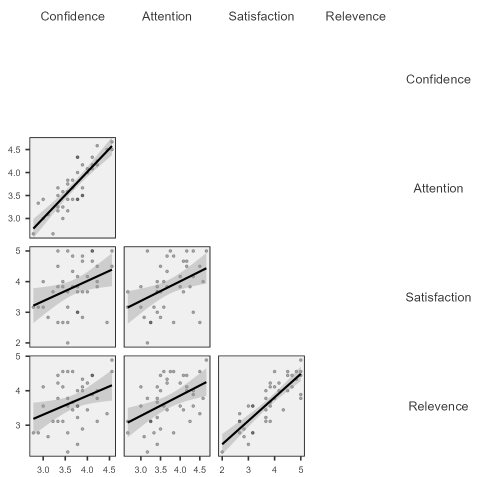


Figure 4. Inter-factors Correlation illustration.

### *4.4. Multi-Linear regression model coefficient - motivation*

After testing the reliability and examining the correlations among the study's dimensions, we proceeded with a multiple linear regression analysis to gain deeper insights into how these four dimensions influence teachers' motivation. The tables below present the results of this analysis.

Table 5. Model Coefficients - Motivation.

| Predictor | Estimate | SE | t | p | hypothesis | Results |
|---|---|---|---|---|---|---|
| **Intercept** | 0.00139 | 0.1200 | 0.0116 | 0.991 | *** | *** |
| **Confidence** | 0.36754 | 0.0579 | 6.3501 | < .001 | H1a | Supported |
| **Attention** | 0.16785 | 0.0507 | 3.3092 | 0.002 | H1b | Supported |
| **Satisfaction** | 0.20211 | 0.0294 | 6.8660 | < .001 | H1c | Supported |
| **Relevance** | 0.26567 | 0.0367 | 7.2388 | < .001 | H1d | Supported |

**SE**: Standard Error

From Table 5, the intercept, with an estimate of 0.00139 (SE = 0.1200, t = 0.0116, p = 0.991), is not statistically significant, indicating that when all predictors are zero, the dependent variable is approximately 0.00139, a value not significantly different from zero. Confidence has an estimate of 0.36754 (SE = 0.0579, t = 6.3501, $p < .001$), showing a positive and statistically significant effect on motivation; for each unit increase in confidence, motivation increases by 0.36754 units, holding other variables constant. Attention's estimate is 0.16785 (SE = 0.0507, t = 3.3092, p = 0.002), indicating a positive and significant effect on motivation, with each unit increase in attention resulting in a 0.16785 unit increase in motivation. Satisfaction, with an estimate of 0.20211 (SE = 0.0294, t = 6.8660, $p < .001$), also positively and significantly affects motivation, leading to a 0.20211 unit increase for each unit rise in satisfaction. Relevance has an estimate of 0.26567 (SE = 0.0367, t = 7.2388, $p < .001$), showing a significant positive effect on motivation, increasing it by 0.26567 units for every unit increase in relevance.

Table 6. Collinearity Statistics.

| VIF | Tolerance |
|---|---|
| *** | *** |
| 3.59 | 0.279 |
| 3.92 | 0.255 |
| 3.20 | 0.313 |
| 3.37 | 0.296 |

**VIF:** Variance Inflation Factor

While Table 6 indicates the degree of multicollinearity among the predictors, Wherein the Confidence has a VIF of 3.59 and a Tolerance of 0.279, indicating moderate multicollinearity that remains within acceptable limits. Attention, with the highest VIF of 3.92 and a Tolerance of 0.255, also shows moderate multicollinearity, which is still within acceptable bounds. Satisfaction, with a VIF of 3.20 and a Tolerance of 0.313, exhibits moderate but not severe multicollinearity. Similarly, Relevance has a VIF of 3.37 and a Tolerance of 0.296, reflecting moderate multicollinearity that falls within acceptable limits.

The predictors can be considered reliable for explaining the variance in the dependent variable (motivation) without the need for corrective measures like removing variables or combining them.

Table 7. Model Fit Measures.

| Model | R | $R^2$ | Adjusted $R^2$ |
|---|---|---|---|
| 1 | 0.986 | 0.973 | 0.970 |

The model fit measures in Table 7 indicate that our regression model is highly effective at explaining the variance in teacher motivation towards ChatGPT. The very high R(0.986) and $R^2$( 0.973) values, along with a slightly adjusted but still high Adjusted $R^2$ (0.970) , suggest that the predictors (Confidence, Attention, Satisfaction, and Relevance) collectively provide a robust explanation for the dependent variable. This supports the validity and reliability of our model in assessing the motivation of teachers based on these dimensions.

### *4.5. The impact of demographic variables on teachers' motivation.*

#### *4.5.1. The impact of the 'GENDER' on teachers' motivation.*

Table 8. Shapiro-Wilk Normality Test.

| | W | p |
|---|---|---|
| Motivation | 0.983 | 0.772 |

Table 9. Homogeneity of Variances Test (Levene's).

| | F | df | df2 | p |
|---|---|---|---|---|
| Motivation | 0.0192 | 1 | 39 | 0.890 |

Since both the normality (Table 8) and homogeneity (Table 9) of variances assumptions are satisfied, we can proceed with the student's t-test to compare the means of the two groups, Male and Female.

Table 10. Independent Samples T-Test of Student.

| | | Statistic | df | p | Hypothesis | Results |
|---|---|---|---|---|---|---|
| **Motivation** | Student's t | -0.161 | 39.0 | 0.873 | H2a | Not supported |

Since the p-value (0.873) is greater than 0.05, we fail to reject the null hypothesis. This means there is no statistically significant difference in motivation between the two groups (male and female teachers). This might imply that gender does not affect teachers' motivation towards using ChatGPT.

#### *4.5.2. The impact of the 'AGE' on teachers' motivation*

Table 11. Shapiro-Wilk Normality Test.

| | W | p |
|---|---|---|
| Motivation | 0.977 | 0.559 |

Table 12. Homogeneity of Variances Test (Levene's).

| | F | df | df2 | p |
|---|---|---|---|---|
| Motivation | 2.20 | 2 | 38 | 0.125 |

Table 13. One-Way ANOVA (Fisher's).

| | | F | df1 | df2 | p | Hypothesis | Results |
|---|---|---|---|---|---|---|---|
| **Motivation** | Fisher's | 0.561 | 2 | 38 | 0.575 | H2b | Not supported |

A p-value= 0.575, which exceeds 0.05, indicates that there is no statistically significant difference in motivation scores across the three age groups (*for more details about age groups see Table 1 above*).

*4.5.3. The impact of the 'TEACHING YEARS' on teachers' motivation.*

Table 14. Shapiro-Wilk Normality Test.

| | W | p |
|---|---|---|
| Motivation | 0.984 | 0.838 |

Table 15. Homogeneity of Variances Test (Levene's).

| | F | df | df2 | p |
|---|---|---|---|---|
| Motivation | 0.164 | 2 | 38 | 0.849 |

Table 16. One-Way ANOVA (Fisher's).

| | | F | df1 | df2 | p | Hypothesis | Results |
|---|---|---|---|---|---|---|---|
| **Motivation** | Fisher's | 0.759 | 2 | 38 | 0.475 | H2c | Not supported |

The p-value = 0.475, which is $> 0.05$, means that there is no statistically significant difference in teachers' motivation across the three teaching years groups (*for more details about teaching years groups see Table 1 above*).

### *4.6. Projects evaluation results.*

Table 17. Projects blind peer evaluation results.

| P.ID | TM | IM | P.ID | TM | IM | P.ID | TM | IM | P.ID | TM | IM | P.ID | TM | IM |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| P01 | 91 | 124 | P10 | 77 | 127 | P19 | 78 | 118 | P28 | 93 | 99 | P37 | 64 | 115 |
| P02 | 70 | 90 | P11 | 89 | 106 | P20 | 100 | 121 | P29 | 89 | 107 | P38 | 104 | 113 |
| P03 | 99 | 108 | P12 | 79 | 96 | P21 | 98 | 111 | P30 | 62 | 120 | P39 | 94 | 117 |
| P04 | 69 | 82 | P13 | 79 | 106 | P22 | 70 | 79 | P31 | 71 | 111 | P40 | 100 | 123 |
| P05 | 103 | 118 | P14 | 102 | 108 | P23 | 69 | 78 | P32 | 101 | 130 | P41 | 86 | 95 |
| P06 | 104 | 126 | P15 | 70 | 99 | P24 | 82 | 118 | P33 | 68 | 92 | | | |
| P07 | 70 | 92 | P16 | 102 | 128 | P25 | 94 | 95 | P34 | 94 | 99 | | | |
| P08 | 97 | 129 | P17 | 65 | 99 | P26 | 101 | 118 | P35 | 80 | 82 | | | |
| P09 | 83 | 100 | P18 | 80 | 87 | P27 | 65 | 76 | P36 | 74 | 85 | | | |

**P.ID: Participant Identifier, TM: Traditional method, IM: Intelligent method.*

The paired samples t-test was conducted to compare the scores of two measures: TM-score and IM-score, in order to verify the hypothesis H3:

Table 18. Paired Samples T-Test.

| | | | statistic | df | p | Hypothesis | Results |
|---|---|---|---|---|---|---|---|
| **TM_score** | **IM_score** | **Student's t** | -9.81 | 40.0 | < .001 | H3 | Supported |

Note. $H_a$ $\mu_{\text{Measure 1 - Measure 2}} < 0$

Table 19. Scores Details.

| | N | Mean | Median | SD | SE |
|---|---|---|---|---|---|
| TM_score | 41 | 84.5 | 83 | 13.7 | 2.14 |
| IM_score | 41 | 105.5 | 107 | 15.8 | 2.46 |

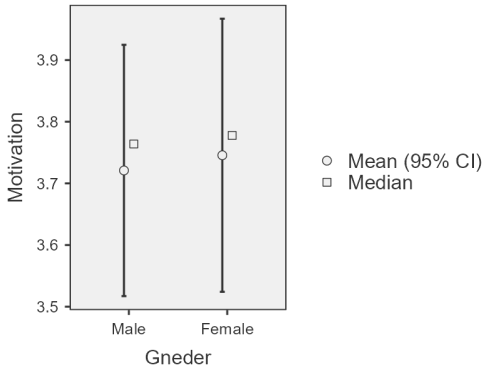


Figure 5. Scores difference representation.

From the Tables (18,19), the negative t-value of -9.81 indicates that there is a significant difference between the TM-score and the IM-score. The degrees of freedom (df) for the test are 40, which is derived from the number of pairs minus one (n - 1). The p-value is less than .001, which is far below the conventional threshold of .05, suggesting that the difference between the two scores is statistically significant.

As illustrated in Figure 5, the alternative hypothesis (H3) tested is that the mean difference between Measure 1 (TM-score) and Measure 2 (IM-score) is less than zero (H3: $\mu_1$ - $\mu_2 < 0$). This indicates that, on average, the TM-scores are significantly lower than the IM-scores.

### *4.7. Results Recap.*

The Table 20 below offers a concise overview of the study's findings, highlighting the varied levels of empirical support for the proposed hypotheses, along with their corresponding sub-hypotheses and outcomes. The first hypothesis (H1) and its four sub-hypotheses (H1a, H1b, H1c, and H1d) were all supported by the results, indicating strong evidence for the proposed relationships. Conversely, the second hypothesis (H2) and its three sub-hypotheses (H2a, H2b, and H2c) were not supported, suggesting a lack of significant evidence for these predictions. Finally, the third hypothesis (H3) was supported, providing confirmation of its associated claims.

Table 20. Summary of hypothesis tested in our study.

| Hypotheses | Sub-hypotheses | Results |
|---|---|---|
| **H1** | H1a | Supported |
| | H1b | Supported |
| | H1c | Supported |
| | H1d | Supported |
| **H2** | H2a | Not Supported |
| | H2b | Not Supported |
| | H2c | Not Supported |
| **H3** | *** | Supported |

## 5. Discussion

The participant teachers in this study demonstrate a positive attitude toward using AI-based tools, which is a promising indicator for the adoption of such technologies in the educational field. This finding is supported by other studies, such as Limna et al. (2023) [47], and Allehyani and Algamdi (2023), who examined Early Childhood Teachers' Beliefs and Perceptions of ChatGPT Applications in the teaching process [48]. Additionally, Ulla et al. (2023) highlight the potential of adopting ChatGPT by exploring EFL teachers' perspectives on this new technology in English language teaching in Thailand [49].

The results confirm that all four predictors (Confidence, Attention, Satisfaction, and Relevance) have a positive and statistically significant impact on motivation. The coefficients in Table 5 indicate the strength and direction of these relationships, showing that higher values in these predictors correspond to greater motivation. This underscores the importance of these dimensions in influencing teacher motivation towards using ChatGPT-4.

Conversely, as shown in Tables (8 – 16), the results did not indicate any significant relationship between teachers' motivation and their gender, age, or years of teaching. This is also confirmed by other studies like Al Darayseh and Fakhar [9, 50].

Moreover, the results demonstrate that the integration of ChatGPT in course preparation significantly enhances the quality of courses, as evidenced by higher IM-scores (Intelligent method) compared to TM-scores (Traditional method) as detailed in Tables (18,19) and represented in Figure 5. Despite a minor deviation from normality in the IM-scores, the statistical analyses consistently support the positive impact of ChatGPT. This result is consistent with the positive findings of other studies on the impact of AI-based educational tools on traditional teaching methods, particularly those by Mohammed, Kooli and Mai DTT [51, 52, 53].

Generally, this positive impact suggests significant potential for incorporating these technologies into continuous professional development (CPD) programs. As recommended by numerous studies including (Neda Arvin et Al; Cecilia Obi Nja et Al; Abdulla Al Darayseh and Firas Almasri), highlighting the necessity of enhancing teachers' digital literacy and preparedness, ensuring equitable access to AI resources, and establishing comprehensive ethical guidelines, leading to enhance their confidence and capabilities in integrating AI technologies in educational contexts [50, 54, 55, 56].

Based on what is discussed above, the statistically significant impact of the factors on motivation in our context, highlights the need for CPD programs to focus on these dimensions. By designing CPD activities that boost teachers' confidence in using AI tools, capture their attention through engaging content, ensure satisfaction by meeting their professional needs, and emphasize the relevance of AI applications in their teaching practice. Integrating AI-based tools -ChatGPT-4- into CPD programs can play a crucial role in professional growth, ultimately leading to improved teaching outcomes and learner engagement.

As we highly recommend for an effective adoption of AI in educational settings, it is imperative that policymakers play a proactive role in providing the necessary materials and facilities for teachers [8]. This includes investing in state-of-the-art technological infrastructure, ensuring widespread access to AI tools. By addressing these needs, policymakers can create an environment where teachers feel supported and equipped to integrate AI into their teaching practices, ultimately enhancing the quality of education and better preparing students for a technologically advanced future.

## 6. Recommendations

To harness this readiness, teacher training programs should be updated to include comprehensive modules on AI literacy, with a focus on practical applications of AI tools like ChatGPT. Training should not only cover the technical aspects of these tools but also pedagogical strategies for integrating AI into the classroom. For instance, professional development workshops can be designed to guide teachers on how to use ChatGPT for lesson planning, personalized student feedback, and generating engaging educational content.

In this context, educational policy makers must evolve to support this integration in schools by creating frameworks that mandate AI literacy as a core component of teacher certification and continuous professional development, including:

- **Developing AI-Centric Curriculum**: Integrating AI into the curriculum at both the pre-service and in-service levels will ensure that teachers are not only users but also innovators in applying AI in their classrooms [57]. For instance, courses on AI and education could become part of teacher education programs, covering both the theoretical and practical aspects of AI integration.
- **Promoting AI-Driven Collaborative Platforms**: Schools and educational institutions can develop collaborative platforms where teachers can share AI-based resources, lesson plans, and best practices. These platforms can also host forums for teachers to discuss challenges and successes in using AI tools, fostering a community of practice that supports continuous learning and improvement.
- **Piloting AI Integration Initiatives**: Governments and educational bodies should consider launching pilot programs to test the integration of AI tools in various educational settings. These pilots can provide valuable data on the effectiveness of AI in enhancing teaching and learning outcomes, which can then inform broader implementation strategies.
- **Supporting Continuous Research and Evaluation**: Continuous research and evaluation should be encouraged to assess the impact of AI on educational outcomes. This can involve longitudinal studies that track the long-term effects of AI integration on student achievement and teacher efficacy. The findings from such research can guide future policy and practice, ensuring that AI tools are used in ways that genuinely enhance educational quality.

Furthermore, policies should encourage the adoption of AI tools by providing funding for the necessary infrastructure, such as high-speed internet and modern digital devices, especially in underserved areas. This will help bridge the digital divide and ensure that all students have equal access to the benefits of AI-enhanced education.

## 7. Conclusion

This study aimed to measure teachers' motivation towards ChatGPT using the IMMS survey, focusing on the dimensions of confidence, attention, satisfaction, and relevance. Our findings indicate that while teachers generally perceive ChatGPT positively across these dimensions, there is no significant relationship between their motivation and demographic variables such as gender, age, or years of experience. These results highlight the universal appeal of AI tools like ChatGPT in educational settings, suggesting that motivational factors are more influenced by individual perceptions of the tool's utility and effectiveness rather than by demographic differences.

Moreover, the study underscores the critical role of policymakers in supporting the integration of AI in education. By providing the necessary resources, infrastructure, and professional development opportunities, policymakers can enhance teachers' readiness and confidence in adopting AI technologies. This support is essential for creating an equitable and effective educational environment where both teachers and students can benefit from the advancements in AI.

Our future research aims to investigate other specific factors that affect teachers' motivation and to develop targeted interventions to promote the adoption of AI in education. Where we will involve a broader sample of teachers from various specialties across all regions of Morocco.

## Study limitations

- One of the study's limitations is the financial means required to support a greater number of teachers. Limited funding restricts the ability to provide access to necessary technological resources (Paid ChatGPT-4). This financial constraint hinders the scalability of the study and the potential to achieve more representative and generalizable results across a broader teacher population.
- Another limitation of the study is the lack of documentation about the integration of ChatGPT in teachers' training. The scarcity of existing literature and empirical studies on this specific application makes it challenging to draw upon established frameworks and best practices. This gap in documentation restricts the ability to contextualize findings within the broader field and underscores the pioneering nature of the research.

REFERENCES


1. Y. Walter, *Embracing the future of Artificial Intelligence in the classroom: the relevance of AI literacy, prompt engineering, and critical thinking in modern education*, International Journal of Educational Technology in Higher Education, vol. 21, no. 1, p. 15, Feb. 2024, DOI: 10.1186/s41239-024-00448-3.
2. K. Tammets and T. Ley, *Integrating AI tools in teacher professional learning: a conceptual model and illustrative case*, Frontiers in Artificial Intelligence, vol. 6, Dec. 2023, DOI: 10.3389/frai.2023.1255089.
3. S. Z. Salas-Pilco, K. Xiao, and X. Hu, *Artificial Intelligence and Learning Analytics in Teacher Education: A Systematic Review*, Education Sciences, vol. 12, no. 8, p. 569, Aug. 2022, DOI: 10.3390/educsci12080569.
4. M. Gunawardena, P. Bishop, and K. Aviruppola, *Personalized learning: The simple, the complicated, the complex and the chaotic*, Teaching and Teacher Education, vol. 139, p. 104429, Mar. 2024, DOI: 10.1016/j.tate.2023.104429.
5. P. Parycek, V. Schmid, and A.-S. Novak, *Artificial Intelligence (AI) and Automation in Administrative Procedures: Potentials, Limitations, and Framework Conditions*, Journal of the Knowledge Economy, pp. 1–26, Jun. 2023, DOI: 10.1007/s13132-023-01433-3.
6. O. Ventista and C. Brown, *Teachers' professional learning and its impact on students' learning outcomes: Findings from a systematic review*, Social Sciences & Humanities Open, vol. 8, p. 100565, May 2023, DOI: 10.1016/j.ssaho.2023.100565.
7. L. Huang, *Ethics of Artificial Intelligence in Education: Student Privacy and Data Protection*, Science Insights Education Frontiers, vol. 16, pp. 2577–2587, Jun. 2023, DOI: 10.15354/sief.23.re202.
8. H. Fakhar, M. Lamrabet, N. Echantoufi, K. E. Khattabi, and L. Ajana, *Towards a New Artificial Intelligence-based Framework for Teachers' Online Continuous Professional Development Programs: Systematic Review*, International Journal of Advanced Computer Science and Applications, vol. 15, no. 4, Art. no. 4, 33/30 2024, DOI: 10.14569/IJACSA.2024.0150450.
9. H. Fakhar, M. Lamrabet, N. Echantoufi, K. Khattabi, and L. Ajana, *Artificial Intelligence from Teachers' Perspectives and Understanding: Moroccan Study*, International Journal of Information and Education Technology, vol. 14, p. 856, Jun. 2024, DOI: 10.18178/ijiet.2024.14.6.2111.
10. H. Fakhar, K. Ouadrhiri, M. Lamrabet, N. Echantoufi, K. E. Khattabi, and L. Ajana, *Teachers' engagement in online continuous professional training programs in Morocco*, International Journal of Multidisciplinary Research and Growth Evaluation, vol. 5, no. 3, pp. 585–594, 2024, DOI: 10.54660/.IJMRGE.2024.5.3.585-594.
11. L. Banh and G. Strobel, *Generative artificial intelligence*, Electronic Markets, vol. 33, no. 1, p. 63, Dec. 2023, DOI: 10.1007/s12525-023-00680-1.
12. A. Aggarwal, M. Mittal, and G. Battineni, *Generative adversarial network: An overview of theory and applications*, International Journal of Information Management Data Insights, vol. 1, no. 1, p. 100004, Apr. 2021, DOI: 10.1016/j.jjimei.2020.100004.
13. J.-T. Chien, *Chapter 7 - Deep Neural Network*, in *Source Separation and Machine Learning*, J.-T. Chien, Ed., Academic Press, 2019, pp. 259–320. DOI: 10.1016/B978-0-12-804566-4.00019-X.
14. I. H. Sarker, *Machine Learning: Algorithms, Real-World Applications and Research Directions*, SN Computer Science, vol. 2, no. 3, p. 160, Mar. 2021, DOI: 10.1007/s42979-021-00592-x.
15. P. P. Shinde and S. Shah, *A Review of Machine Learning and Deep Learning Applications*, in *2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA)*, Aug. 2018, pp. 1–6. DOI: 10.1109/ICCUBEA.2018.8697857.
16. R. Pugliese, S. Regondi, and R. Marini, *Machine learning-based approach: global trends, research directions, and regulatory standpoints*, Data Science and Management, vol. 4, pp. 19–29, Dec. 2021, DOI: 10.1016/j.dsm.2021.12.002.
17. L. Alzubaidi et al., *Review of deep learning: concepts, CNN architectures, challenges, applications, future directions*, Journal of Big Data, vol. 8, no. 1, p. 53, Mar. 2021, DOI: 10.1186/s40537-021-00444-8.
18. T. Talaei Khoei, H. Ould Slimane, and N. Kaabouch, *Deep learning: systematic review, models, challenges, and research directions*, Neural Computing and Applications, vol. 35, no. 31, pp. 23103–23124, Nov. 2023, DOI: 10.1007/s00521-023-08957-4.
19. D. Jurafsky and J. H. Martin, *Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition*, 3rd Ed. draft, Stanford University, 2024.
20. T. Young, D. Hazarika, S. Poria, and E. Cambria, *Recent Trends in Deep Learning Based Natural Language Processing [Review Article]*, IEEE Computational Intelligence Magazine, vol. 13, no. 3, pp. 55–75, Aug. 2018, DOI: 10.1109/MCI.2018.2840738.
21. M. E. Bernal, *Revolutionizing eLearning Assessments: The Role of GPT in Crafting Dynamic Content and Feedback*, Journal of Artificial Intelligence Technology, May 2024, DOI: 10.37965/jait.2024.0513.

22. M. Farrokhnia, S. K. Banihashem, O. Noroozi, and A. Wals, *A SWOT analysis of ChatGPT: Implications for educational practice and research*, Innovations in Education and Teaching International, vol. 61, no. 3, pp. 460–474, May 2024, DOI: 10.1080/14703297.2023.2195846.
23. C. Zhu, M. Sun, J. Luo, T. Li, M. Wang, and X. X., *How to harness the potential of ChatGPT in education?*, Knowledge Management & E-Learning: An International Journal, vol. 15, no. 2, Art. no. 2, May 2023.
24. M. Javaid, A. Haleem, R. P. Singh, S. Khan, and I. H. Khan, *Unlocking the opportunities through ChatGPT Tool towards ameliorating the education system*, BenchCouncil Transactions on Benchmarks, Standards and Evaluation, vol. 3, no. 2, p. 100115, Jun. 2023, DOI: 10.1016/j.tbench.2023.100115.
25. M. J. Reiss, *The use of AI in education: Practicalities and ethical considerations*, London Review of Education, vol. 19, no. 1, 2021, DOI: 10.14324/LRE.19.1.05.
26. Del Siegle, *A Role for ChatGPT and AI in Gifted Education*, Gifted Child Today, vol. 46, no. 3, pp. 211–219, Jun. 2023, DOI: 10.1177/10762175231168443.
27. A. Harry, *Role of AI in Education*, Interdiciplinary Journal of Humanity Injury, vol. 2, no. 3, pp. 260–268, Mar. 2023, DOI: 10.58631/injurity.v2i3.52.
28. F. Flores Limo et al., *Personalized tutoring: ChatGPT as a virtual tutor for personalized learning experiences*, Przestrzeń Społeczna, vol. 23, pp. 293–312, Jun. 2023.
29. L. Ding, T. Li, S. Jiang, and A. Gapud, *Students' perceptions of using ChatGPT in a physics class as a virtual tutor*, International Journal of Educational Technology in Higher Education, vol. 20, no. 1, p. 63, Dec. 2023, DOI: 10.1186/s41239-023-00434-1.
30. L. Kohnke, B. Moorhouse, and D. Zou, *ChatGPT for Language Teaching and Learning*, RELC Journal, vol. 54, Apr. 2023, DOI: 10.1177/00336882231162868.
31. M. Javaid, A. Haleem, R. P. Singh, S. Khan, and I. H. Khan, *Unlocking the opportunities through ChatGPT Tool towards ameliorating the education system*, BenchCouncil Transactions on Benchmarks, Standards and Evaluation, vol. 3, no. 2, p. 100115, Jun. 2023, DOI: 10.1016/j.tbench.2023.100115.
32. R. R. Molefi, M. A. Ayanwale, L. Kurata, and J. Chere-Masopha, *Do in-service teachers accept artificial intelligence-driven technology? The mediating role of school support and resources*, Computers & Education: Open, vol. 6, p. 100191, Jun. 2024, DOI: 10.1016/j.caeo.2024.100191.
33. A. Iyamuremye et al., *Utilization of artificial intelligence and machine learning in chemistry education: a critical review*, Discover Education, vol. 3, no. 1, p. 95, Jul. 2024, DOI: 10.1007/s44217-024-00197-5.
34. S. Choi, Y. Jang, and H. Kim, *Influence of Pedagogical Beliefs and Perceived Trust on Teachers' Acceptance of Educational Artificial Intelligence Tools*, International Journal of Human-Computer Interaction, vol. 39, no. 4, pp. 910–922, Feb. 2023, DOI: 10.1080/10447318.2022.2049145.
35. L. Chen, P. Chen, and Z. Lin, *Artificial Intelligence in Education: A Review*, IEEE Access, vol. 8, pp. 75264–75278, 2020, DOI: 10.1109/ACCESS.2020.2988510.
36. I. H. Y. Yim and J. Su, *Artificial intelligence (AI) learning tools in K-12 education: A scoping review*, Journal of Computers in Education, Jan. 2024, DOI: 10.1007/s40692-023-00304-9.
37. A. Almusaed, A. Almssad, I. Yitmen, and R. Z. Homod, *Enhancing Student Engagement: Harnessing 'AIED's Power in Hybrid Education—A Review Analysis*, Education Sciences, vol. 13, no. 7, Jul. 2023, DOI: 10.3390/educsci13070632.
38. I. Gligorea, M. Cioca, R. Oancea, A.-T. Gorski, H. Gorski, and P. Tudorache, *Adaptive Learning Using Artificial Intelligence in e-Learning: A Literature Review*, Education Sciences, vol. 13, no. 12, Dec. 2023, DOI: 10.3390/educsci13121216.
39. H. A. El-Sabagh, *Adaptive e-learning environment based on learning styles and its impact on development students' engagement*, International Journal of Educational Technology in Higher Education, vol. 18, no. 1, p. 53, Oct. 2021, DOI: 10.1186/s41239-021-00289-4.
40. J. Siddharth, P. Vanshika, G. Vinit Kumar, and N. Vivek, *An Automated Grading System*, International Research Journal of Modern Engineering and Technology Science, vol. 5, no. 11, 2023.
41. Y. Rakibi et al., *The Analysis of Earth and Life Sciences Educational Videos in TelmidTice Platform (Morocco): Technical Quality, Pedagogical and Didactic Considerations*, International Journal of Information and Education Technology, vol. 14, no. 5, pp. 732–744, 2024, DOI: 10.18178/ijiet.2024.14.5.2098.
42. A. Jurane-Bremane, *Peer Assessment in Adult Education: Challenges and Opportunities*, Social Integration Education Proceedings of the International Scientific Conference, vol. 5, p. 148, May 2019, DOI: 10.17770/sie2019vol5.3919.
43. A. Julien, E. Romijn, and A. Schmeding, *Peer and self-evaluation as a tool in teacher education*, 2023, DOI: 10.13140/RG.2.2.13083.64803.
44. Y. Zhang and C. D. Schunn, *Self-regulation of peer feedback quality aspects through different dimensions of experience within prior peer feedback assignments*, Contemporary Educational Psychology, vol. 74, p. 102210, Jul. 2023, DOI: 10.1016/j.cedpsych.2023.102210.
45. *Sharing good practice: Strategies to encourage teacher collaboration*, Iris Connect. Accessed: May 15, 2024. [Online]. Available: https://blog.irisconnect.com/uk/sharing-and-collaboration-in-schools.
46. J. M. Keller, *The Arcs Model of Motivational Design*, in Motivational Design for Learning and Performance: The ARCS Model Approach, J. M. Keller, Ed., Boston, MA: Springer US, 2010, pp. 43–74. DOI: 10.1007/978-1-4419-1250-3_3.
47. P. Limna, T. Kraiwanit, K. Jangjarat, P. Klayklung, and P. Chocksathaporn, *The Use of ChatGPT in the Digital Era: Perspectives on Chatbot Implementation*, Journal of Applied Learning & Teaching, vol. 6, Jun. 2023, DOI: 10.37074/jalt.2023.6.1.32.
48. S. Allehyani and M. Alghamdi, *Digital Competences: Early Childhood Teachers' Beliefs and Perceptions of ChatGPT Application in Teaching English as a Second Language (ESL)*, International Journal of Learning, Teaching and Educational Research, Nov. 2023, DOI: 10.26803/ijlter.22.11.18.
49. M. B. Ulla, W. F. Perales, and S. O. Busbus, *To generate or stop generating response': Exploring EFL teachers' perspectives on ChatGPT in English language teaching in Thailand*, Learn. Res. Pract., vol. 9, no. 2, pp. 168–182, Jul. 2023, DOI: 10.1080/23735082.2023.2257252.

50. A. Al Darayseh, *Acceptance of artificial intelligence in teaching science: Science teachers' perspective*, Comput. Educ. Artif. Intell., vol. 4, p. 100132, Jan. 2023, DOI: 10.1016/j.caeai.2023.100132.
51. A. M. Mohamed, *Exploring the potential of an AI-based Chatbot (ChatGPT) in enhancing English as a Foreign Language (EFL) teaching: perceptions of EFL Faculty Members*, Educ. Inf. Technol., vol. 29, Jun. 2023, DOI: 10.1007/s10639-023-11917-z.
52. C. Kooli, *Chatbots in Education and Research: A Critical Examination of Ethical Implications and Solutions*, Sustainability, vol. 15, no. 7, Art. no. 7, Jan. 2023, DOI: 10.3390/su15075614.
53. D. T. T. Mai, C. V. Da, and N. V. Hanh, *The use of ChatGPT in teaching and learning: a systematic review through SWOT analysis approach*, Front. Educ., vol. 9, Feb. 2024, DOI: 10.3389/feduc.2024.1328769.
54. C. O. Nja et al., *Adoption of artificial intelligence in science teaching: From the vantage point of the African science teachers*, Smart Learn. Environ., vol. 10, no. 1, p. 42, Sep. 2023, DOI: 10.1186/s40561-023-00261-x.
55. F. Almasri, *Exploring the Impact of Artificial Intelligence in Teaching and Learning of Science: A Systematic Review of Empirical Research*, Res. Sci. Educ., Jun. 2024, DOI: 10.1007/s11165-024-10176-3.
56. N. Arvin, M. Hoseinabady, B. Bayat, and E. Zahmatkesh, *Teacher Experiences with AI-based Educational Tools*, AI Tech Behav. Soc. Sci., vol. 1, pp. 26–32, Apr. 2023, DOI: 10.61838/kman.aitech.1.2.5.
57. M. LAMRABET, H. FAKHAR, N. ECHANTOUFI , K.E. KHATTABI, L. AJANA, *AI-Based Tools: Exploring the Perceptions and Knowledge of Moroccan Future Teachers Regarding AI in the Initial Training - A case study -*, International Journal of Information and Education Technology, Vol 14, No. 11, 2024, DOI: 10.18178/ijiet.2024.14.11.2180

# Appendix

## Appendix A: Blind Peer Evaluation Grill

Participant ID: . . .

| Domaine | Criteria | Notation | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Traditional method | | | | | Intelligent method | | | | |
| | | 1 | 2 | 3 | 4 | 5 | 1 | 2 | 3 | 4 | 5 |
| Presentation Objectives | The learning objectives are specified. | | | | | | | | | | |
| | The learning objectives are properly formulated. | | | | | | | | | | |
| | The learning objectives are clear. | | | | | | | | | | |
| | The learning objectives align with the pedagogical guidelines. | | | | | | | | | | |
| Presentation Content | The content appropriately aligns with the conceptual and methodological goals established by the official texts. | | | | | | | | | | |
| | The content is scientifically precise. | | | | | | | | | | |
| | The content is linguistically accurate. | | | | | | | | | | |
| | The content avoids unnecessary repetitions. | | | | | | | | | | |
| | The content is well-organized. | | | | | | | | | | |
| Pedagogical Side | The introduction successfully engages the student's interest. | | | | | | | | | | |
| | The sequence of learning activities follows a logical progression. | | | | | | | | | | |
| | The activities necessitate active involvement from the learner. | | | | | | | | | | |
| | The activities effectively stimulate the learner's motivation and enthusiasm. | | | | | | | | | | |
| | The activities foster learning autonomy. | | | | | | | | | | |
| | The activities require interactive engagement. | | | | | | | | | | |
| | The activities encourage collaborative learning among students. | | | | | | | | | | |
| | The documents are presented with clarity. | | | | | | | | | | |
| | The explanations provided are sufficient to facilitate understanding. | | | | | | | | | | |
| | The synthesis of the presented elements is executed well. | | | | | | | | | | |
| Visual Media | The slides are free from clutter. | | | | | | | | | | |
| | The images are clear and sharp. | | | | | | | | | | |
| | The text (characters/fonts) is easily readable. | | | | | | | | | | |
| | The design (colors and graphics) is visually appealing. | | | | | | | | | | |
| | The audio and video are synchronized. | | | | | | | | | | |
| | There are no visual obstructions. | | | | | | | | | | |
| | Visual engagement is evident | | | | | | | | | | |
| Final Score | | | | | | | | | | | |

*1: Poor, 2: Unsatisfactory, 3: Satisfactory, 4: Very satisfactory, 5: Outstanding.*

## Appendix B: List of topics

| Ref | Nbr of teachers | Topic | Task |
|---|---|---|---|
| T1 | 03 | Mechanic | Moment of a force |
| T2 | 03 | | Equilibrium of a solid body capable of rotating about a forced axis |
| T3 | 03 | | Archimedes' Thrust |
| T4 | 03 | | Working with a force: translation/rotation |
| T5 | 03 | | Mechanical Oscillator |
| T6 | 03 | Electricity | Concept of Electric Current: Metals/Electrolyte Solution |
| T7 | 03 | | Interpretation of the characteristics of certain electrical poles |
| T8 | 03 | | Transistor |
| T9 | 03 | | Voltage: Direct/Sinusoidal Alternating |
| T10 | 03 | Waves | The conductivity of a solution |
| T11 | 03 | | Waves: Mechanical/Electromagnetic |
| T12 | 03 | Lenses | Thin lenses |
| T13 | 04 | | Calorimetry (Thermodynamics) |