

Teachers Behavior in the AI Assessment Tools Adoption in Morocco: A Diffusion of Innovation and Technology Using PLS-SEM

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Abstract—Artificial Intelligence (AI) is increasingly shaping educational practices and assessment systems worldwide. However, the mechanisms through which AI-based assessment tools diffuse among teachers remain insufficiently understood, particularly in developing-country contexts. Drawing on both the Technology Acceptance Model (TAM) and the Diffusion of Innovation perspective, this study examines the factors influencing teachers' adoption of AI tools for Life and Earth Sciences (LES) assessment in Moroccan public secondary schools. In this framework, diffusion is operationalized through teachers' exposure to AI tools, training and digital literacy, and perceived institutional and pedagogical constraints that shape the spread of AI-supported assessment practices. A quantitative survey was conducted among secondary school teachers in the Rabat-Sale-Kenitra region of Morocco. The proposed conceptual model was tested using Partial Least Squares Structural Equation Modeling (PLS-SEM). The measurement model demonstrated acceptable internal consistency and construct reliability, while the structural model exhibited substantial explanatory power for the key endogenous constructs. The findings indicate that teachers' attitudes toward AI play a central mediating role in the adoption process. Attitude is primarily influenced by the perceived impact of AI on learning outcomes, followed by perceived usefulness and perceived ease of use. Consistent with TAM assumptions, attitude significantly influences behavioral intention, which in turn emerges as the strongest predictor of actual AI use in assessment practices. Despite generally favorable perceptions of AI, the results reveal a substantial intention-use gap, as most teachers report rarely or never using AI tools in classroom assessment. Overall, the study contributes to the literature on AI adoption in education by integrating diffusion-related factors with technology acceptance mechanisms in a developing-country context. The findings highlight the importance of teacher training, digital competence development, and supportive institutional environments for facilitating the sustainable diffusion of AI-supported assessment practices.

Keywords—Artificial Intelligence (AI) adoption, teachers, diffusion of innovation, Technology Acceptance Model (TAM), Partial Least Squares Structural Equation Modeling (PLS-SEM), educational assessment, Life and Earth Sciences (LES)

I. INTRODUCTION

Technology has profoundly transformed nearly all aspects of contemporary life, and education is no exception [1]. Educational systems worldwide are increasingly transitioning toward the use of fifth-generation internet technologies and

the Internet of Things (IoT), accompanied by a growing interest in the integration of Artificial Intelligence (AI) applications in teaching, learning, and assessment [2]. The importance of AI in education has intensified considerably, particularly following the widespread closure of schools and universities during the COVID-19 pandemic, which accelerated the adoption of digital and AI-enabled solutions [3]. As a result, AI is increasingly shaping educational practices, driving the development of learning management systems, assessment tools, and intelligent learning support mechanisms [4, 5].

Recent research on AI-based learning environments suggests that expanding opportunities for learning through advanced digital applications enhances the capacity of educational systems to innovate and adapt to evolving societal demands [6]. Given the multifaceted roles AI can play across the teaching learning continuum, it holds substantial potential to influence both learners' present experiences and their future competencies [7, 8]. The rapid expansion of internet-based technologies has further facilitated access to information for teachers and students, underscoring the need to capitalize on AI applications in curriculum design, instructional strategies, and assessment practices to promote more effective learning outcomes [9].

Despite the considerable promise of AI-supported learning, its widespread availability does not automatically translate into effective classroom implementation, particularly in science education [10]. The successful integration of AI depends heavily on teachers' preparedness, pedagogical competencies, and willingness to adopt innovative practices. International reports highlight that many educators remain insufficiently equipped to implement AI-based teaching and assessment approaches, raising concerns about instructional quality and equity [11]. Moreover, the adoption of educational technologies is closely linked to teachers' attitudes toward innovation. A segment of educators continues to view classroom technology integration with skepticism, preferring traditional teaching materials and methodologies. Such apprehension toward novel instructional tools can significantly hinder meaningful technology adoption [12].

Although AI applications are increasingly promoted as transformative tools for educational development and assessment, important gaps remain in understanding the

mechanisms that shape teachers' adoption of AI-based assessment tools, particularly in developing-country contexts [13]. Existing studies have largely focused on technologically advanced educational systems and often examine AI integration in general teaching and learning environments rather than in assessment practices specifically [14]. As a result, limited empirical evidence exists regarding how teachers' perceptions, pedagogical beliefs, and professional readiness influence the adoption of AI-supported assessment tools within resource-constrained educational systems [15].

Moreover, although models such as the Technology Acceptance Model (TAM) identify perceived usefulness and perceived ease of use as key determinants of technology adoption, their mediating mechanisms in the context of AI-based educational assessment remain insufficiently explored. In particular, little empirical research has examined how these determinants interact with contextual factors such as training, digital literacy, and perceived institutional constraints to influence teachers' attitudes, behavioral intentions, and actual use of AI in assessment practices

In Morocco, digital transformation occupies a central position in national strategies aimed at modernizing the education system [16]. Initiatives such as Morocco Digital 2025 emphasize the integration of information and communication technologies across sectors, including education [17]. However, the extent to which AI adoption in assessment functions as a disruptive force or as a catalyst for educational development remains an open empirical question. The literature presents contrasting perspectives: while some studies emphasize AI's potential to enhance efficiency, innovation, and learning outcomes, others warn of risks related to equity, pedagogical dependence, and the potential erosion of students' analytical autonomy during assessment processes [18].

Empirical evidence from Morocco further reveals sectoral disparities in AI-driven educational transformation [19]. Private schools have made relatively rapid progress in adopting digital and AI-supported solutions, whereas public schools have experienced slower and more uneven advancement [20]. This lag is often attributed to infrastructural constraints, coordination challenges, and limited Information and Communications Technology (ICT) adoption among public-sector educators. Comparative experiences from countries such as Estonia and Singapore demonstrate that successful AI integration in public education requires more than technological investment alone; it depends on the development of a supportive ecosystem encompassing robust infrastructure, coherent national strategies, adaptive regulatory frameworks, and effective public-private partnerships [21].

Against this backdrop, the present study examines the role of AI in facilitating assessment practices in Life and Earth Sciences (LES) within public schools in the Rabat-Sale-Kenitra region of Morocco, where AI integration continues to face persistent challenges. Despite ongoing efforts to advance educational digitalization, multiple barriers continue to hinder the effective and sustained use of AI in assessment. As Morocco seeks to accelerate its digital transformation and modernize educational assessment practices, the emergence of advanced digital technologies is expected to fundamentally

reshape information exchange and instructional delivery. In this context, the study addresses the following research questions:

- (1) Which factors influence teachers' adoption of AI in educational assessment in the Rabat-Sale-Kenitra region?
- (2) How do teachers' attitudes, training, and perceived barriers shape AI adoption in assessment practices?
- (3) What is the impact of digitalization on teachers' satisfaction with AI-based assessment tools?
- (4) How does training and digital literacy contribute to teachers confidence and acceptance of AI in educational assessment?
- (5) What challenges and opportunities characterize AI-driven transformation in Moroccan public schools?

II. LITERATURE REVIEW

A. Artificial Intelligence (AI)

This section basically supports the background section by providing evidence for the proposed hypothesis. This section should be more comprehensive and thoroughly describe all the studies that you have mentioned in the background section. It should also elaborate on all studies that form evidence for the present study and discuss the current trends.

To write this section, you will need to do a thorough literature search on different studies that relate to the broad topic of your research. This will introduce the readers to the area of your research. It would be ideal to organize them thematically and discuss them chronologically so that readers are aware of the evolution and progress in the field. In other words, separate themes should be discussed chronologically to highlight how research in those fields has progressed over time. This will highlight what has been done and what are the future directions that need to be worked upon.

AI refers to a class of computer systems inspired by the functioning of human neural processes involved in understanding, learning, reasoning, and decision-making [22]. The foundational premise of AI is that human intelligence can be described with sufficient precision to enable its simulation by machines. In its most advanced forms, AI exhibits capabilities analogous to human learning, pattern recognition, problem-solving, and natural language communication [23]. What fundamentally distinguishes AI from conventional computer programs is its ability to learn and adapt autonomously. Despite its rapid development, AI remains an emerging concept with substantial potential to evolve and enhance the efficiency of resource utilization across multiple sectors [24].

Education represents one of the most prominent domains for AI application. AI has increasingly been recognized as a core component of Science, Technology, Engineering, and Mathematics (STEM) education, supporting teachers in their roles as facilitators, evaluators, and instructional designers [25]. This contribution is particularly evident through the analysis of large-scale educational data generated by students, teachers, and institutions [26]. For instance, Connor *et al.* [27] reported a successful primary-level mathematics intervention in which individualized instructional strategies were developed based on automated analyses of learning data collected from 32 teachers and 370 students. Another widely adopted application is the

educational chatbot an AI-driven system capable of recognizing and processing natural language to provide context-appropriate responses and personalized learning support across digital platforms such as computers, mobile devices, and smart speakers [28, 29].

Well-known examples include Amazon Alexa and Google Home. Interaction between learners and chatbots has been shown to foster engagement and support the emergence of innovative pedagogical paradigms across scientific disciplines [30].

Empirical evidence suggests that AI-based instructional approaches positively influence students' academic performance and contribute to reducing learning challenges such as vocabulary attrition [31]. Similarly, chatbots have demonstrated effectiveness in science education by enhancing learners' understanding and performance [32]. Moreover, AI-supported scaffolding systems employed by teachers have been found to improve STEM students' scientific writing skills [33].

AI applications possess advanced capabilities for receiving, storing, and processing information, while simultaneously promoting self-directed learning. These features enable science teachers to better accommodate individual learner differences, thereby improving instructional quality and educational outcomes [34]. AI also facilitates the integration and organization of learners' conceptual knowledge, supports interactive presentation of scientific content, and contributes to achieving remedial and enrichment objectives aligned with students' needs [35]. A wide range of AI-based software solutions is available for both autonomous and teacher-guided learning, supporting discussion, collaboration, and knowledge exchange, which collectively enhance the overall educational process [36]. Consequently, AI applications exert a transformative influence on curriculum design, teaching methodologies, assessment practices, and educational communication. Key areas of AI application in education include:

- Intelligent tutoring systems, which simulate one-to-one human instruction by delivering personalized learning activities and immediate, constructive feedback tailored to learners' cognitive needs [37].
- Adaptive learning environments, which customize content presentation according to individual learning styles and preferences, using techniques such as fuzzy logic, Bayesian networks, hidden Markov models, and genetic algorithms [38].
- AI-based assessment systems, which automate test design, grading, and performance evaluation to guide learners' subsequent learning pathways [39].
- Smart content development, whereby AI supports the digitization of textbooks, creation of interactive learning interfaces, and development of educational robots capable of generating high-quality digital resources [40].
- Virtual Reality (VR) technologies, which integrate AI-driven immersive environments into teaching, offering multisensory learning experiences that enhance conceptual understanding, learner autonomy, and exploratory learning.

In science education specifically, a variety of AI-supported tools are increasingly utilized, including Physics Education Technology (PhET) simulations, Labster Virtual Labs, and

Third Space platforms. Tan *et al.* [41] found that mobile learning applications represent the most frequently used AI tools among teachers, followed by online professional development platforms, while automated grading systems are also adopted to a lesser extent.

B. Attitude toward AI (ATT)

Attitude toward artificial intelligence refers to teachers' overall positive or negative evaluation of AI-based tools in educational assessment. In technology adoption research, attitude is considered a key psychological antecedent influencing individuals' willingness to accept and use new technologies [42]. A favorable attitude typically reflects perceived pedagogical value, relevance to professional practice, and alignment with educational objectives.

The descriptive results indicate that teachers hold a generally positive conceptual perception of AI, with nearly half defining it as a technology capable of simulating human intelligence and a majority recognizing its benefits for personalized feedback and assessment efficiency [43]. Furthermore, the strong endorsement of hybrid AI human assessment models suggests that teachers perceive AI as a supportive tool rather than a threat to professional autonomy. Based on this reasoning, teachers with more positive attitudes toward AI are expected to demonstrate stronger intentions to adopt AI in LES assessment [44].

H1: Attitude toward AI (ATT) has a significant positive effect on teachers' Behavioral Intention (BI) to use AI in LES assessment.

C. Training and Literacy (TL)

Training and digital literacy represent teachers' level of knowledge, skills, and preparedness to effectively use AI-based tools in assessment practices. Prior research consistently highlights training as a critical enabler of educational technology adoption, particularly for advanced systems such as AI [45].

The empirical findings reveal a substantial training gap, with the vast majority of teachers reporting no prior training in AI for assessment, despite expressing strong willingness to receive such training. This lack of preparedness appears to constrain both confidence and experimentation with AI tools, even among teachers who recognize their pedagogical value. Training and literacy are therefore expected to influence adoption indirectly by shaping teachers' attitudes and intentions toward AI use [45].

H2: Training and Literacy (TL) have a significant positive effect on teachers' Attitude toward AI (ATT).

H3: Training and Literacy (TL) have a significant positive effect on teachers' Behavioral Intention (BI) to use AI in LES assessment.

D. Perceived Barriers (PB)

Perceived barriers refer to teachers' perceptions of obstacles that hinder AI integration into assessment, such as lack of time, insufficient resources, limited institutional support, or difficulties integrating AI into pedagogical routines [46]. These barriers represent contextual and operational constraints rather than individual resistance. Previous studies clearly indicate that perceived barriers are highly salient, with lack of training and lack of resources or time identified as the dominant impediments to AI adoption.

Additionally, the very low frequency of AI use in LES assessment suggests that these barriers significantly weaken the transition from intention to actual use. Accordingly, perceived barriers are expected to negatively affect both teachers' intentions and their actual engagement with AI tools.

H4: Perceived Barriers (PB) have a significant negative effect on teachers' Behavioral Intention (BI) to use AI.

H5: Perceived Barriers (PB) have a significant negative effect on the Actual Use (AU) of AI-based assessment tools.

E. Perceived Ease of Use (PEOU) and Exposure

Perceived ease of use and exposure reflect the extent to which teachers consider AI tools easy to understand, accessible, and compatible with their level of digital familiarity. Exposure through commonly used tools such as smart spreadsheets or digital assessment platforms can reduce uncertainty and foster gradual acceptance [47]. The literature review shows a strong preference for simple, familiar tools, particularly AI-enhanced spreadsheets, which suggests that ease of use and prior exposure strongly condition teachers' willingness to adopt AI. Conversely, limited exposure to more advanced AI tools may explain teachers' cautious perceptions regarding students' analytical autonomy. Thus, perceived ease of use and exposure are expected to positively influence both attitudes and intentions toward AI adoption [48].

H6: Perceived Ease of Use (PEOU) and exposure have a significant positive effect on teachers' Attitude toward AI (ATT).

H7: Perceived Ease of Use (PEOU) and exposure have a significant positive effect on teachers' Behavioral Intention (BI) to use AI.

F. Perceived Impact on Learning (PIL)

Perceived impact on learning refers to teachers' beliefs regarding AI effects on students' learning outcomes, autonomy, and analytical skills. In educational technology adoption, perceived pedagogical impact is a critical determinant of acceptance, particularly in assessment contexts [49]. These ambivalent perceptions suggest that perceived learning impact may function as a decisive factor in shaping adoption intentions. Teachers who perceive AI as enhancing learning quality and assessment fairness are therefore more likely to develop stronger behavioral intentions.

H8: Perceived Impact on Learning (PIL) has a significant positive effect on teachers' Behavioral Intention (BI) to use AI in LES assessment.

G. Behavioral Intention and Actual Use

Behavioral intention represents teachers' readiness and willingness to use AI-based tools, while actual use reflects the concrete implementation of these tools in assessment practices. In line with the Technology Acceptance Model (TAM), behavioral intention is considered the most immediate determinant of actual technology use. Within the broader perspective of Diffusion of Innovation theory, intention can also be interpreted as an intermediate stage in the adoption process through which teachers move from awareness and evaluation of an innovation toward its practical implementation. In this study, diffusion-related

factors such as training opportunities, exposure to AI tools, and perceived institutional barriers shape teachers' perceptions and attitudes, which in turn influence their behavioral intentions and subsequent use of AI-based assessment tools. Although current usage levels remain limited, the reported openness to experimentation and strong endorsement of AI-assisted assessment suggest that behavioral intention constitutes a key mechanism through which AI-supported assessment practices may gradually diffuse within educational settings, particularly when institutional support and professional training are strengthened [50].

H9: Behavioral Intention (BI) has a significant positive effect on the Actual Use (AU) of AI-based tools in LES assessment.

Based on the Technology Acceptance Model and previous studies on educational technology adoption, the conceptual framework assumes that teachers' perceptions of AI tools influence their attitudes toward AI, which in turn shape their behavioral intentions and ultimately determine actual use of AI-based assessment tools. The proposed conceptual model therefore integrates cognitive determinants (PU, PEOU, PIL), contextual factors (TL, PB), and attitudinal and intentional mechanisms (ATT and BI) to explain teachers' adoption of AI in assessment practices.

Recent scholarship suggests that the integration of AI in education has evolved from early emphasis on automation and intelligent tutoring toward broader concerns related to teacher agency, assessment redesign, ethics, and institutional readiness [51]. In Global South contexts, this evolution is especially significant because AI adoption unfolds under conditions of uneven infrastructure, limited professional development opportunities, and variable policy support. Emerging reviews published in 2025 and 2026 indicate that although AI is increasingly recognized as a tool for personalization, assessment support, and pedagogical innovation, its implementation remains highly uneven across educational systems, particularly where teacher AI competence and institutional capacity are still developing [52, 53]. International evidence therefore suggests that the adoption of AI in assessment should be understood not only as a question of perceived usefulness, but also as a function of training, governance, infrastructure, and contextual equity.

This perspective is particularly relevant for the present study. While TAM provides a strong basis for explaining how perceived usefulness and perceived ease of use shape attitudes and intentions, recent research suggests that these mechanisms may operate differently across teacher subgroups and institutional settings [54]. Variables such as professional experience, school context, and level of exposure to digital tools may condition how teachers translate favorable perceptions into actual classroom practice. For that reason, demographic heterogeneity should not be treated as merely descriptive, but as a potentially important source of variation in AI adoption trajectories.

III. MATERIALS AND METHODS

A. Data Collection

In this study, the target population included LES teachers

employed in public schools in Rabat-sale-Kenitra, Morocco, during the 2025/2026 academic year. Data were collected via an online questionnaire developed in consultation with ten in-service teachers, yielding 427 completed responses. Before the main deployment, a pilot test was conducted to assess the questionnaire content validity, clarity, and formatting, ensuring consistency with the study objectives. The pilot data were excluded from the final analyses.

The sample size was determined using Slovin's formula in order to ensure adequate representativeness, with a 5% margin of error and a 95% confidence level [55]. Given the limited number of teachers integrating AI into assessment practices in our region, a sample of 427 valid respondents was considered sufficient. A voluntary sampling technique was adopted. The questionnaire was distributed via teachers' WhatsApp groups and other professional social media channels between January 15 and March 5, 2025. Data collection focused on teachers' perceptions regarding the adoption of artificial intelligence in LES assessment practices. The questionnaire was revised for linguistic clarity and layout quality, then translated into French to improve accessibility and response quality.

A total of 446 responses were submitted. After data screening, 19 responses were excluded because of missing or inconsistent data, and 427 valid responses were retained for analysis. This corresponds to a usable response rate of 95.7% among submitted questionnaires. Since the questionnaire was distributed online through professional groups and could be shared across different networks, the exact number of teachers who received or viewed the questionnaire link could not be precisely determined. Therefore, the overall non-response rate could not be accurately calculated. This limitation was considered when interpreting the generalizability of the findings.

B. Survey Design

Based on prior work on technology adoption in education [56], we designed a questionnaire tailored to the integration of AI in science assessment at the secondary level adapted to the Rabat-Sale-Kenitra region situation. The instrument used in the current study comprised 15 questions and was organized into three sections.

The first section of the questionnaire presented the study aims and provided brief information about demographic and professional characteristics of respondents: gender, work context, years of science-teaching experience, teaching cycle (Middle school and High school), and levels currently taught. These variables were used as control variables in the structural model to account for demographic and professional differences among respondents. No formal moderation analysis was conducted in the present study.

The questionnaire included items measuring the main constructs derived from the TAM adapted to AI-based educational assessment. These constructs include PU, PEOU, TL, PB, PIL, ATT, BI, and AU.

All constructs were operationalized using reflective indicators measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), or from 1 (never) to 5 (very often) when referring to frequency of use. The measurement items were adapted from established technology adoption studies and adjusted to the context of

AI-based assessment in secondary education (Table 1).

To address the specific nature of LES assessment, the measurement items were revised to explicitly refer to LES-related assessment practices, including scientific reasoning, interpretation of graphs, analysis of experimental results, and feedback on biological and geological concepts.

Table 1. Measurement items

Construct	Measurement item	Source
PU	AI improves the efficiency of assessment activities in Life and Earth Sciences.	TAM adapted
PU	AI improves the quality of feedback provided to students in LES assessment.	TAM
PEOU	AI tools used for LES assessment are easy to understand.	TAM
PEOU	AI tools are easy to integrate into LES teaching and assessment practices.	TAM
TL	I feel confident using AI tools to assess LES learning activities.	AI literacy literature
TL	LES teachers should receive specific training on AI-based assessment tools.	Technology adoption studies
PB	Lack of resources limits the integration of AI into LES assessment.	Educational technology studies
PB	Lack of time prevents the use of AI tools in LES assessment activities	Educational technology studies
PIL	AI improves students' understanding of LES concepts and scientific reasoning.	Educational technology
PIL	AI helps analyze students' performance in interpreting scientific data, graphs, and experimental results.	Educational technology
ATT	Using AI in LES assessment is beneficial for teaching.	TAM
ATT	I have a positive attitude toward using AI in LES assessment.	TAM
BI	I intend to use AI tools in my future LES assessments.	TAM
BI	I plan to integrate AI tools into my LES teaching and assessment practices.	TAM
AU	Frequency of AI use in LES assessment practices.	Technology adoption

C. Data Analysis

In this study, the proposed research framework was examined using Structural Equation Modeling (SEM). SEM offers a robust and integrative analytical approach for testing hypothesized relationships between latent constructs and their observed indicators [57]. By combining elements of path analysis, factor analysis, and multiple regression within a unified causal framework, SEM enables the simultaneous estimation of both the measurement model and the structural model, thereby providing a comprehensive assessment of complex theoretical relationships [58].

The measurement items employed in the questionnaire were adapted from established studies on technology acceptance and adoption [59]. Given the quantitative nature of the research design, SPSS and SmartPLS were jointly utilized for data analysis to ensure analytical rigor and precision.

Although the sample size of the study ($N = 427$) would also permit Covariance-Based Structural Equation Modeling (CB-SEM), the Partial Least Squares Structural Equation

Modeling (PLS-SEM) approach was selected for several reasons. First, the research aims to explore the determinants of AI adoption in educational assessment within a relatively under-researched context, which justifies a prediction-oriented analytical approach. Second, the conceptual framework includes multiple constructs and mediation relationships, increasing the structural complexity of the model. Third, several constructs were measured with a limited number of indicators, a situation for which PLS-SEM is particularly suitable. For these reasons, PLS-SEM was considered an appropriate analytical technique for examining the predictive relationships among teachers' perceptions, attitudes, behavioral intentions, and actual use of AI-based assessment tools.

Prior to model estimation, the dataset underwent a systematic data-screening and cleaning procedure to address potential issues arising from data collection. This process involved the identification and exclusion of incomplete, inconsistent, or extreme responses, in line with recommended data-monitoring practices in empirical research [60]. Such preprocessing steps ensured the suitability of the dataset for subsequent statistical analyses.

To assess the potential influence of non-response bias, an early-versus-late respondent comparison was conducted. In survey-based research, late respondents are commonly treated as a proxy for non-respondents. The first and last waves of valid responses were compared across key demographic variables and the main study constructs using independent-sample tests. The results showed no statistically significant differences between early and late respondents at the 0.05 level. Therefore, non-response bias was not considered a major threat to the validity of the findings.

Following data preparation, a reliability assessment was conducted on the 15 measurement items included in the survey instrument. Cronbach's alpha was used to evaluate internal consistency reliability, reflecting the degree to which items within each construct are interrelated. Cronbach's alpha is widely regarded as a fundamental indicator of scale reliability, with higher values generally suggesting that the items consistently measure the same underlying construct. However, the interpretation of alpha values depends on several factors, including the number of items in the scale, the magnitude of inter-item correlations [61], and the conceptual homogeneity of the construct being measured (Eqs. (1) and (2)).

$$\alpha = \frac{K}{K-1} \left(1 - \frac{\sum_{i=1}^K \sigma_{Y_i}^2}{\sigma_X^2} \right) \quad (1)$$

where:

K = is the number of items,
 σ_X^2 = is the variance of the total score,
 $\sigma_{Y_i}^2$ = is the variance of the item

$$Y = \beta_0 + \beta_1 \times PU + \beta_2 \times PB + \beta_3 \times TL + \beta_4 \times PEOU + \beta_5 \times PLI + \beta_6 \times ATT + \beta_7 \times BI + \beta_8 \times AU + \varepsilon \quad (2)$$

where:

Y = IA Adoption
 PB = Perceived barriers
 TL = Training and Literacy

$PEOU$ = Exposure

PIL = Impact on Learning

ATT = Attitude toward IA

BI = Perceived Intention

AU = Actual Use

ε = Error term

The relationships among latent constructs variables that cannot be directly observed were examined by distinguishing between exogenous and endogenous variables within the SEM framework. Depending on its position in the model, a construct may function simultaneously as an independent and a dependent variable. The system of structural equations specifies all hypothesized relationships between exogenous and endogenous constructs, while explicitly accounting for measurement error in the observed indicators. SEM offers a robust analytical framework for investigating complex theoretical models, as it enables the simultaneous estimation of both direct and indirect effects among variables. This capability is particularly valuable for uncovering mediated relationships and interdependencies that would be difficult to detect using traditional statistical techniques [62].

IV. RESULT AND DISCUSSION

A. Reliability Test

Internal consistency reliability was assessed by comparing the estimated α values with the commonly accepted threshold of 0.70 [63]. For the present study, the 15-item measurement scale achieved a Cronbach's alpha of 0.746, exceeding the recommended cutoff and indicating satisfactory internal consistency [64] (Table 2). This result suggests that the items consistently capture the underlying construct and provides strong support for the robustness of the measurement model.

The observed reliability level aligns with established methodological standards and prior empirical research, thereby strengthening the credibility of the subsequent analyses related to AI adoption in educational assessment within the Rabat-Sale-Kenitra region of Morocco. Furthermore, the stability of the alpha coefficient across the scale confirms the coherence of the measurement instrument and supports the overall quality of the dataset. In addition, the findings reveal meaningful associations between the key explanatory variables, namely training, available resources, perceived complexity, and compatibility, and the outcome variable, AI-based assessment adoption, underscoring the relevance of the selected constructs.

Table 2. Reliability test

Cronbach's Alpha	Number of elements
0.746	15

B. Demographic Characteristics of Respondents

As summarized in Table 2, descriptive statistics indicated that the sample was composed predominantly of female participants (73%), whereas men represented 27 % of the respondents. Regarding the workplace environment, the majority of teachers worked in urban areas (58.2%), while 41.8% were employed in rural settings, suggesting diverse professional contexts that may influence teaching conditions and pedagogical practices.

In terms of professional experience, most participants reported between 5 and 10 years of service (44.5%), followed

by teachers with less than 5 years of experience (23.1%). A smaller proportion was between 10 and 20 years (19.1%) or between 20 and 30 years of experience (13.2%), while only 0.2% had more than 20 years. This distribution reflects a workforce that is relatively young in terms of seniority.

Table 3. Demographic characteristics of respondents

Variable	Statistic	Variables	Participants	Frequency
T1: Gender		Female	311	73.005
		Men	115	26.995
T2: Workplace		Urban	248	58.216
		Rural	178	41.784
T3: Experience		<5 years	98	23.059
		Between 5 to 10 years	189	44.471
		Between 10 to 20 years	81	19.059
		Between 20 to 30 years	56	13.176
		>20 years	1	0.235
T4: Educational cycles		Secondary college	152	35.681
		Vocational secondary education	219	51.408
		both	55	12.911
T5: Levels currently taught		Non-certifying	172	40.376
		Certifying	254	59.624

Regarding the educational cycles taught, more than half of the respondents (51.4%) worked in vocational secondary education, while 35.7% taught in secondary college, and 12.9% reported teaching in both cycles. Finally, 59.6% of participants were responsible for certifying levels, compared to 40.4% who taught non-certifying levels, which may

influence evaluation practices and academic pressure (Table 3).

C. Characteristics of AI Adoption in LES Assessment

Descriptive statistics show that, in the context of assessment in LES, most teachers (47.9%) perceived AI as a technology capable of simulating human intelligence, while 35.2% viewed it as a versatile tool applicable across multiple domains, including education. A smaller proportion associated AI with specific applications such as chatbots, facial recognition, or voice assistants (13.1%), and only 3.8% limited their understanding to educational robotics (Table 4). These results reflect a generally broad and conceptually advanced perception of AI among respondents.

With respect to prior preparation, a large majority (87.8%) reported having received no training but expressed a willingness to develop AI-related skills, whereas 8.0% were not interested in training. Only a small minority reported basic (3.8%) or advanced (0.5%) training, highlighting a substantial professional-development gap in AI integration for assessment. Regarding tools already used in classroom assessment, more than half of the respondents (53.1%) indicated that they had not yet experimented with AI tools but were open to doing so, while others reported using conversational AI (19.2%), digital assessment platforms (16.4%), or data-analysis tools (11.3%) (Table 4).

Table 4. Characteristics of AI adoption

Variable	Variables	Participants	Frequency
Q1: What does AI represent for you in the context of assessment in LES?	Educational robotics only.	16	3.756
	A tool used in several fields (education...).	150	35.211
	A set of applications such as voice assistants, facial recognition, chatbots, etc.	56	13.146
	A technology that enables machines to mimic human intelligence.	204	47.887
Q3: Have you received training in AI or educational technology relevant to assessment?	Yes, in-depth training.	2	0.469
	Yes, basic training.	16	3.756
	No, but I would like training.	374	87.793
	No, and I am not interested.	34	7.981
Q4: Which AI tools have you already tested for classroom assessment?	Digital assessment applications (e.g., Kahoot, Nearpod, Quizizz, MagicSchool, Wordwall).	70	16.432
	Data analysis tools (e.g., Excel).	48	11.268
	I have not yet tested any AI tools, but I am interested in using them.	226	53.052
	ChatGPT or other conversational AI tools.	82	19.249
Q6: Which AI tools would you recommend for analyzing assessment results?	Data analysis.	12	2.817
	Smart spreadsheets (Excel with AI, Google Sheets).	376	88.263
	Statistical analysis software (e.g., SPSS, R with AI).	28	6.573
	Identifying gaps.	6	1.408
	I haven't tested any AI tools yet, but I'm interested in using them.	4	0.939
Q7: Have you observed improvements in students' analytical skills when they use AI in LES?	Yes, they are more independent in interpreting results.	32	7.512
	Yes, but it depends on the tool used.	18	4.225
	No, it does not change their level.	242	56.808
	No, they become more dependent on technology.	134	31.455
Q8: In your view, what are the principal advantages of using AI in LES assessment?	AI helps adapt assessment to students' individual levels.	42	9.859
	AI assists in the analysis and interpretation of assessment data.	124	29.108
	AI enables quick correction and simplifies the assessment process.	44	10.329
	AI supports individualized student monitoring and personalized feedback.	216	50.704

Concerning tools recommended for analyzing assessment results, a strong majority (88.3%) favored smart spreadsheet

solutions (e.g., Excel with AI), whereas fewer respondents opted for statistical software (6.6%), general data-analysis applications (2.8%), or gap-analysis tools (1.4%). A small proportion (0.9%) had not yet used any tools but showed interest (Table 4). Regarding the perceived impact of AI on students' analytical skills, most respondents reported either no improvement (56.8%) or greater dependence on technology (31.5%), while only a minority observed increased independence (7.5%) or tool-dependent outcomes (4.2%) (Table 4).

Finally, the perceived advantages of AI in LES assessment were primarily associated with personalized monitoring and feedback (50.7%), followed by enhanced data analysis and interpretation (29.1%), faster grading processes (10.3%), and improved adaptation to individual learner levels (9.9%). Overall, the findings suggest that teachers clearly recognize the benefits of AI for personalization and assessment efficiency, yet these advantages remain constrained by limited training and uneven classroom adoption (Table 4).

D. Characteristics of Innovation

According to Table 5, the main factors hindering AI integration into educational assessment were a lack of training in AI use (50.2%) and insufficient resources or time

(44.6%), while institutional/administrative constraints were less frequently cited (2.8%); a small additional share again referenced training-related gaps (2.3%). This distribution indicates that capacity-building and resourcing issues outweigh structural constraints in the eyes of respondents.

Regarding frequency of use, most teachers reported never using AI tools in LES assessment (79.8%), with smaller proportions using them once a month (15.0%), once a week (4.7%), or every day (0.5%). This pattern suggests that, despite the visibility of AI in education, classroom adoption remains limited.

When asked about specific difficulties encountered, the majority highlighted lack of teacher training (75.6%), followed by lack of student interest (12.7%) and difficulty integrating tools into assessment (11.7%). These results reinforce training as the dominant operational hurdle.

Finally, recommendations for successful integration showed a near-consensus in favor of combining AI with human assessment to personalize learning and ensure fairness (94.8%), with minimal support for AI-only correction (1.4%), cheating detection only (3.3%), or fully replacing teachers (0.5%). This strong convergence reflects a clear preference for hybrid, human-in-the-loop models that prioritize equity and pedagogical judgment (Table 5).

Table 5. Characteristics of innovation

Variable	Variables	Participants	Frequency
Q2: What factors hinder your integration of AI into educational assessment?	Institutional or administrative constraints.	12	2.817
	Lack of training in the use of artificial intelligence in assessment.	214	50.235
	Lack of resources or appropriate tools and lack of time.	190	44.601
	Lack of training in the use of artificial intelligence in assessment.	10	2.347
Q5: How frequently do you use AI tools in your LES assessments?	Never.	340	79.812
	Once a week.	20	4.695
	Once a month.	64	15.023
	Every day.	2	0.469
Q9: What specific difficulties have you encountered when integrating AI into your LES assessments?	Lack of interest among students.	54	12.676
	Lack of teacher training.	322	75.587
	Difficulty integrating these tools into school assessment.	50	11.737
Q10: What recommendations would you make for the successful integration of AI into LES assessment?	Use AI to correct written assignments only.	6	1.415
	Combine AI and human assessment to personalize learning and ensure fairness.	402	94.811
	Use AI solely to detect cheating.	14	3.302
	Replace teachers entirely with AI tools.	2	0.472

E. Measurement Model

The structural relationships among the study variables were examined using the PLS-SEM technique. PLS-SEM is particularly suitable for analyzing complex models and theoretical frameworks that remain insufficiently validated in prior research [65]. In addition, this approach explicitly accounts for measurement error, thereby producing more robust and reliable parameter estimates compared to conventional regression-based methods [66]. Given the exploratory nature and conceptual complexity of the modified UMEGA model an area that has received limited empirical attention the use of PLS-SEM was considered methodologically appropriate.

The analysis was conducted using SmartPLS 4.0, a software package widely validated in empirical studies involving structural model assessment [67]. Compared with covariance-based SEM tools such as AMOS, which are primarily designed for confirmatory analysis [68], SmartPLS provides superior functionality for estimating total and indirect effects. This capability is particularly relevant in the present study, as it enables a detailed examination of AI

adoption in LES assessment through attitudinal pathways and allows for the assessment of cumulative indirect effects among the model constructs.

To evaluate the reliability and validity of the measurement model, multiple quality criteria were applied, as summarized in Tables 6 and 7. Table 6 reports key indicators, including factor loadings, Cronbach's alpha (α), Composite Reliability (CR), and Average Variance Extracted (AVE). Factor loadings exceeding 0.70 are generally considered indicative of adequate indicator reliability [69]. In this study, standardized loadings ranged from 0.705 to 0.897, thereby satisfying the recommended threshold. Moreover, no cross-loading issues were detected, as all indicators loaded more strongly on their respective constructs than on any other latent variable, confirming appropriate item assignment.

Internal consistency reliability was assessed using both Cronbach's alpha and composite reliability. Cronbach's alpha values approached or exceeded the recommended minimum of 0.70, ranging from 0.694 to 0.751. Likewise, composite reliability values, which are considered acceptable when exceeding 0.60 and preferable above 0.70 ranged from 0.675 to 0.739, confirming satisfactory construct reliability.

Convergent validity was examined through the AVE criterion, with values above 0.50 indicating that a construct explains more than half of the variance of its indicators [70]. As reported in Table 6, AVE values ranged between 0.508 and 0.567, meeting this requirement. Discriminant validity was assessed using the Fornell–Larcker criterion (Table 7), which requires the square root of a construct's AVE to exceed

its correlations with other latent variables [71]. The results confirm that this condition was met for all constructs, thereby establishing discriminant validity.

Overall, these findings provide strong empirical support for the reliability and validity of the measurement model, ensuring a solid foundation for the subsequent evaluation of the structural model and hypothesis testing [72].

Table 6. Cronbach's alpha, composite reliability, and Average Variance Extracted (AVE)

Variables	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)	Square root of AVE	CR	Factor Loadings
PU	0.711	0.691	0.549	0.743	0.776	0.709 to 0.836
PB	0.722	0.709	0.546	0.739	0.805	0.711 to 0.844
TL	0.694	0.682	0.567	0.746	0.813	0.714 to 0.802
PEOU	0.701	0.683	0.542	0.708	0.878	0.752 to 0.886
PIL	0.751	0.739	0.518	0.720	0.819	0.705 to 0.821
ATT	0.704	0.675	0.512	0.665	0.836	0.718 to 0.843
BI	0.733	0.715	0.508	0.708	0.801	0.744 to 0.811
AU	0.719	0.707	0.521	0.685	0.874	0.767 to 0.897

Table 7. Correlation matrix and square root of AVE

Variables	PU	PB	TL	PEOU	PIL	ATT	BI	AU	Square root of AVE
PU	1								0.743
PB	0.68	1							0.739
TL	0.65	0.44	1						0.746
PEOU	0.59	0.61	0.47	1					0.708
PIL	0.51	0.56	0.56	0.42	1				0.720
ATT	0.29	0.29	0.52	0.31	0.37	1			0.665
BI	0.58	0.55	0.59	0.52	0.58	0.65	1		0.708
AU	0.65	0.53	0.62	0.60	0.59	0.66	0.72	1	0.685

Finally, to address potential concerns regarding common method bias, Harman's single-factor test was applied to the dataset. Consistent with the procedure recommended in prior methodological research [73], an exploratory factor analysis with an unrotated factor solution was conducted using SPSS. The results indicated that the extracted factors jointly accounted for 63.4% of the total variance, while the largest proportion of variance explained by a single factor was limited to 36.6%. Importantly, no single factor exceeded the commonly accepted threshold of 50%, suggesting that common method variance does not constitute a significant threat to the validity of the findings. These outcomes provide additional evidence supporting the soundness and robustness of the measurement model.

F. Structural Model and Hypothesis Testing

Table 8 summarizes the results of the structural model estimated through the PLS-SEM approach. The model demonstrates strong explanatory power, accounting for approximately 67.9% of the variance in the endogenous constructs, which is considered high according to Latan and Ramli [74]. As presented in Table 8, most hypothesized paths were statistically significant at the 0.05 level, confirming the predictive strength of the proposed framework for AI adoption in assessment practices among teachers. The path from PU $\rightarrow$ ATT exhibited the strongest standardized coefficient ($\beta = 0.324$, $t = 3.153$, $p < 0.01$), indicating that teachers' positive attitudes toward integrating artificial intelligence in evaluation are mainly shaped by their perception of its usefulness (Fig. 1).

The influence of PB on Attitude was statistically significant ($\beta = 0.211$, $t = 2.917$, $p > 0.05$), suggesting that, although constraints such as lack of resources or training exist, they do not decisively shape teachers' attitudes toward AI adoption. However, TL had a significant but weaker positive effect on Attitude ($\beta = 0.158$, $t = 1.384$, $p < 0.05$),

highlighting the importance of digital competence and awareness programs in strengthening acceptance.

Table 8. Outcomes of hypotheses

Hypothesis	Construct link	Std path coef	Critical ratio	Signif. (p)	Supported
1	PU $\rightarrow$ ATT	0.324	3.153	$p < 0.003$	Y
2	PB $\rightarrow$ ATT	0.211	2.917	$p < 0.105$	N
3	TL $\rightarrow$ ATT	0.158	1.384	$p < 0.021$	Y
4	PEOU $\rightarrow$ ATT	0.198	2.541	$p < 0.003$	Y
5	PIL $\rightarrow$ ATT	0.459	3.925	$p < 0.043$	Y
6	ATT $\rightarrow$ BI	0.527	5.012	$p < 0.002$	Y
7	BI $\rightarrow$ AU	0.785	19.615	$p < 0.001$	Y
8	CO $\rightarrow$ AU	-0.264	2.128	$p < 0.001$	Y

Note: $p < 0.05$.

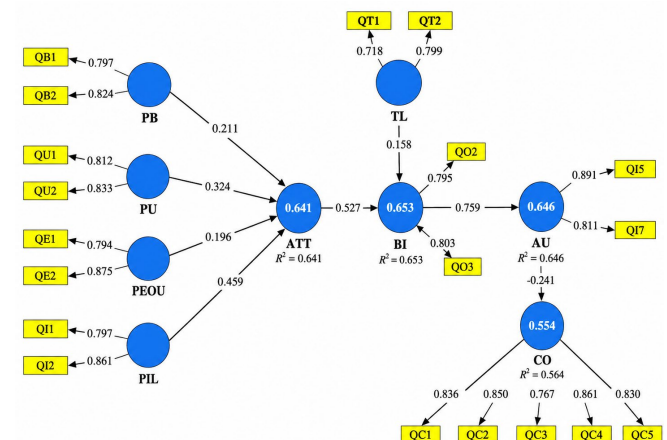


Fig. 1. Path analysis results of the structural model.

Similarly, PEOU showed a significant contribution to Attitude ($\beta = 0.198$, $t = 2.541$, $p < 0.01$), confirming that simplicity and accessibility remain decisive in shaping favorable perceptions of AI tools. The strongest effect on Attitude was observed for PIL ($\beta = 0.459$, $t = 3.925$, $p < 0.05$),

underlining that teachers' belief in AI's potential to enhance learning outcomes substantially improves their attitudes toward its integration.

Downstream, Attitude significantly influenced BI ($\beta = 0.527, t = 5.012, p < 0.01$), while Behavioral Intention strongly predicted AU ($\beta = 0.785, t = 19.615, p < 0.001$), confirming the mediating mechanism consistent with the TAM. The control path CO $\rightarrow$ AU was also significant and negative ($\beta = -0.264, t = 2.128, p < 0.001$), suggesting that demographic and contextual factors (gender, workplace, experience, educational cycle, and level taught) may moderate actual AI use.

Overall, these results indicate that attitudinal and intentional determinants play central roles in explaining AI adoption behaviors, while barriers have limited direct influence. The model confirms the robustness and predictive validity of the proposed framework for understanding teachers' engagement with AI-based assessment tools in Moroccan educational contexts.

G. Model Quality Indicators: R^2 and Predictive Relevance (Q^2)

The quality of the proposed model was evaluated using two key indicators: the coefficient of determination (R^2) and predictive relevance (Q^2). The R^2 statistic is widely employed to assess a model's explanatory power, as it reflects the proportion of variance in the endogenous constructs explained by the exogenous variables. As reported in Table 8, the model achieved an overall R^2 value of 68.6%, indicating that a substantial share of the variance in the dependent constructs is accounted for by the independent variables.

At the construct level, behavioral intention explained 62.8% of the variance in teachers' intention to adopt AI-based assessment, while perceived barriers, perceived usefulness, perceived impact on learning, training, and literacy, and perceived ease of use/exposure collectively explained 64.3% of the variance in attitude toward AI adoption. These values demonstrate strong explanatory power and meet the thresholds recommended in the literature [75, 76].

In addition to explanatory capacity, the model's predictive performance was assessed using the Stone-Geisser Q^2 statistic, which evaluates the ability of the model to predict endogenous constructs through a cross-validated redundancy approach. Q^2 values greater than zero indicate predictive relevance, whereas values equal to or below zero suggest limited predictive capability. As shown in Table 9, all Q^2 values for the endogenous constructs exceeded zero, confirming the predictive relevance of the proposed model and supporting its capacity to generate accurate predictions in accordance with established methodological guidelines [77].

Although the results show that teachers generally hold favorable attitudes toward artificial intelligence, these positive perceptions do not automatically translate into frequent classroom use. This finding points to an important intention-use gap in the adoption process. From the perspective of the Technology Acceptance Model, positive attitudes and behavioral intentions are necessary but not sufficient conditions for actual use, particularly when the technology requires pedagogical adaptation and sustained institutional support. In other words, teachers may recognize the usefulness of AI and remain open to its potential, while

still being unable or unwilling to integrate it regularly into assessment practices [78].

This discrepancy can also be interpreted through the Diffusion of Innovation perspective. Positive attitudes may indicate that many teachers have reached the stages of awareness, interest, and evaluation of AI-based assessment tools, but have not yet progressed fully to trial, implementation, and reutilization. The descriptive findings support this interpretation, as a large proportion of respondents expressed interest in AI and acknowledged its benefits, yet most reported little or no practical use. This suggests that adoption is slowed not by rejection of the innovation itself, but by the absence of enabling conditions that would allow teachers to move from conceptual acceptance to sustained pedagogical application [79].

Several contextual factors help explain this gap. First, the strong lack of prior training indicates that many teachers may value AI conceptually while lacking the technical and pedagogical competence required for effective implementation [80]. Second, limited resources, time constraints, and uneven institutional support may reduce teachers' capacity to experiment with AI tools in authentic assessment settings [81]. Third, concerns about students' dependence on technology and the uncertain impact of AI on analytical skills may contribute to cautious adoption, especially in a subject such as Life and Earth Sciences, where interpretation, reasoning, and scientific autonomy are central learning objectives [82].

Taken together, these results suggest that AI adoption in Moroccan public schools remains at an early and transitional stage, in which positive attitudes create potential for diffusion, but structural and pedagogical barriers continue to hinder regular use. Therefore, successful AI integration in assessment depends not only on teachers' favorable perceptions, but also on the availability of training opportunities, practical exposure, pedagogical guidance, and supportive institutional conditions capable of transforming intention into actual and sustainable use. Therefore, the study suggests that successful AI integration in assessment depends not only on teachers' favorable perceptions, but also on the availability of training opportunities, practical exposure, pedagogical guidance, and institutional conditions that can transform intention into actual and sustainable use.

Table 9. Indicators of model quality

Variables	R^2	Q^2
ATT	0.643	0.501
BI	0.628	0.530
AU	0.686	0.584

V. CONCLUSION

This study examined the determinants of teachers' adoption of AI-based assessment tools in LES education within Moroccan public secondary schools. Although artificial intelligence is increasingly recognized as a promising instrument for improving assessment practices, the findings reveal that its actual classroom use remains limited despite generally positive perceptions among teachers. This discrepancy highlights a persistent gap between favorable attitudes toward AI and its effective pedagogical implementation.

Drawing on an extended Technology Acceptance Model

analyzed through PLS-SEM, the results demonstrate that teachers' attitudes toward AI constitute the central mechanism driving adoption. Perceived impact on learning, perceived usefulness, perceived ease of use, and training-related factors significantly shape attitudes, which in turn influence behavioral intention and ultimately actual use. These findings confirm that AI adoption in educational assessment remains primarily intention-driven and strongly dependent on teachers' professional readiness and institutional support.

From a theoretical perspective, this study contributes to the literature by extending technology acceptance research to the context of AI-supported educational assessment in developing-country environments. By integrating attitudinal mechanisms with contextual determinants such as training and institutional constraints, the proposed framework provides a more comprehensive understanding of how AI-based innovations diffuse within educational systems undergoing digital transformation.

From a practical standpoint, the results underscore the importance of targeted professional training, improved digital competencies, and supportive institutional ecosystems to facilitate the sustainable integration of AI into assessment practices. A further limitation concerns the absence of a formal moderation analysis. Although demographic and professional variables were included as controls, this study did not test whether these variables moderated the relationships between attitudes, behavioral intention, and actual AI use. Future research should examine such moderating effects using interaction terms or multi-group analysis. Future research should extend this framework across different disciplines, educational levels, and national contexts, and adopt longitudinal approaches to better capture the evolution of teachers' adoption behaviors over time.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Conceptualization, S.B., B.J., M.L.M., and H.A.; methodology, S.B.; O.A and S.C.; software, S.B.; O.A and S.C.; validation, S.B., B.J., M.L.M., H.A., and O.A; formal analysis, S.B.; investigation, S.B and S.C.; resources, S.B.; B.J., M.L., O.A.; H.A and S.C.; data curation, S.B.; writing-original draft preparation, S.B.; writing-review and editing, S.B., O.A., and S.C.; visualization, S.B.; supervision, O.A, and S.C.; project administration, S.B. and S.C.; funding acquisition, S.B. All authors had approved the final version.

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