Adoption, for a Course Preparation and Assessment, of Generative AI in Moroccan Public University Institutions: A Multi-institutional Survey

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***Abstract*—To sum up, that study investigates the impact of the generative AI adoption through different factors influencing the adoption of Generative Artificial Intelligence (AI) in the preparation of courses and the development of assessments by Moroccan university teachers. That study hereby gathers four hundred faculty members from eleven Moroccan public universities. It is a comparison between Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) using binary logistic regression. The model performance is assessed by using Akaike Information Criterion (AIC) and Area Under the Curve (AUC) metrics. It indicates that AI is much more used for course preparation, at a percentage of 59.3%. Besides, assessment creation represents 43.5%. Those statistics are different because it has to keep an intact academic integrity and AI hallucinations. The faculty uses AI to simplify complex ideas and create new ones. The statistic results indicate that the TAM is, by far, the best predictor in AI adoption. If it is compared to the UTAUT, the AIC and the AUC indicators are higher (AIC = 184.27, AUC = 0.94) than UTAUT (AIC = 480.82, AUC = 0.61). To conclude, Moroccan faculty members consider the use of AI pragmatic and individualistic. It emphasizes on the institutions need to establish professional programs, dedicated to development and transparent assessment practices, considering AI integration.**

***Keywords*—generative artificial intelligence, higher education, Morocco, Technology Acceptance Model (TAM), teacher Artificial Intelligence (AI) adoption, course preparation, assessment design**

I. Introduction

Recently, there was a transition in generative Artificial Intelligence (AI) tools. They became widely used, after having been tested. These capabilities can be useful to higher education staff when they are using this technology to accomplish time-consuming tasks, such as creating lecture materials, providing examples of complex subjects and revising assessments [1]. However, since generative AI outputs may contain convincingly incorrect data, may recreate the bias from the training data, and may create authoring boundary problems when the output is utilized without disclosed attribution, the emergence of these tensions requires an understanding of whether instructors are adopting AI and how/under what conditions they view that use as beneficial versus risky.

The evidence from around the world indicates that the course design has major uptake but more circumspect (or cautious) uptake in aspects of assessment. The research evidence indicates that university teaching practitioners are routinely using AI to generate explanations, structure courses, and assist with student feedback. However, many academics are less willing to use AI for generating and marking high-stakes exams without thoroughly reviewing the content since the validity of the assessment is closely related to the alignment of the assessment with the learning objectives, level of difficulty, and equity of the assessment process across different groups of students. The patterns of uptake are also influenced by the presence of institutional protocols and programs for training faculty, which clarify acceptable uses of AI, provide support for verification practices, and lessen confusion about how to ensure academic integrity and eliminate bias in grading [2].

Morocco is similar to other countries in having growing interest in generative Artificial Intelligence (AI), as well as undergoing a broad-based transformation of digital technologies for higher education. Higher education institutions in Morocco teach students in several languages and students have different academic backgrounds: therefore, there is a need for clarity in explanations and numerous examples to support learning. Additionally, the professors do not have enough time to test and experiment with new concepts, the access to training is often random, and there is little clarity on how to incorporate AI into testing (e.g., fairness, security, curriculum alignment). At this point, empirical data related to these practices is very limited by comparison across multiple institutions [3].

This research seeks to fill the gap in previous research by using data from a cross-sectional survey of 400 respondents from 11 public universities in Morocco. Unlike previous descriptive studies used in the prior literature, this study will apply a comparative model approach to study the competing constructs of the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) using Binary Logistic Regression to compare the two TAM and UTAUT. Through the use of Akaike Information Criterion (AIC) and Area Under the Curve (AUC) measures, this study will help to determine which theoretical framework is the most robust in predicting the adoption of Artificial Intelligence (AI) within the institutions of higher education in Morocco [4], using these same metrics will help to establish baseline data for professional development and the development of policy for the integration of AI into institutions of higher education in Morocco based on empirical evidence rather than anecdotal evidence.

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II. Literature Review

A. AI Integration and Adoption Drivers

Generative AI's use in higher education is often discussed in the context of productivity tools to assist with writing, ideation, and content creation. A systematic review of AI tools for teachers found that these tools enhance workflow for both planning and providing feedback, but the benefit of those tools relies upon how outputs are validated and contextualized to local teaching curricula and the needs of students [5]. Furthermore, empirical studies show that instructors typically use AI tools for low risk or preparatory tasks, rather than delegating final decisions regarding students' work to AIs, reflecting an effort to respond to both the practical possibilities and limitations of these systems [2].

As for the rationale for adopting AI tools in the classroom, an explanation can typically be framed in terms of the technology acceptance model, where the perceived usefulness and ease of use of the tool informs the intention to use that tool. In most cases, the perceived usefulness of a particular AI tool relates to the time saved with using that tool in comparison to traditional teaching, while the perceived ease of use often relates to how well the AI tool's interface has been designed, the extent to which users are able to easily understand how to use the tool and access reliable AI tools. Research related to the trust that teachers have in using AI-powered educational technology indicates that supporting the professional development of teachers can help to provide teachers with better access to calibrating their trust in how AI tools function, as well as understand which types of AI tools require more monitoring by the teacher [6].

B. Teacher Readiness and Organisational Support

Have consistently been identified as vital factors in the uptake of responsible Artificial Intelligence (AI). Instructors with a high level of self-efficacy in using AI tools will feel comfortable experimenting with them, critically interpreting output and will also be inclined to incorporate the use of these tools into their existing pedagogical practice. Organisational circumstances such as clearly defined usage policies, access to approved tools and opportunities for peer-to-peer learning will reduce uncertainty about use and increase the safety of experimentation. The absence of guidance can result in an increased amount of work required to verify information and increased perceived risk associated with using the AI technology [7, 8].

Current evidence in Morocco indicates that there exists a generally favorable attitude towards AI technology, but there are wide discrepancies in the technical knowledge of teachers and concerns about responsible use. Studies examining the use of AI by Moroccan teachers, as well as the application of AI in higher education in Morocco indicate the need for capacity development and governance to ensure that the use of AI technologies is inclusive in nature and does not compromise the privacy or academic integrity of individuals [8, 9]. The use of AI in multilingual environments may allow for the rephrasing or translation of information; however, the risk increases if the level of performance of the models varies by language or when cultural concepts are represented unintentionally.

C. Assessment, Integrity and Governance

The field of evaluation is unique, as there are implications for career advancement, certification, and institutional credibility for each type of evaluation assignment. Research on assessment in higher education indicates that some instructors use AI primarily to support activities such as refining question wording or clarifying questions, but frequently do not rely on AI for the creation of final examinations due to concerns relating to the validity, bias, and documentation of the evaluations produced [10].

The results of international surveys and discussions about policy indicate that higher education institutions should include support for assessment redesigns in addition to providing guidance on appropriate uses for AI in assessments that promote higher-order thinking as well as authentic applications of learning [11]. Where students have access to generative AI, assessment designs that rely solely on reproduction of information become more vulnerable, increasing interest in in-class tasks, oral examinations, or assignments requiring local data and personal reflection.

D. Research Design and Model Selection.

We have selected both the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) because they both provide two distinct but complementary perspectives on the adoption of technology. The focus of the TAM is at an individual's level, concentrating on how they view the usefulness and ease of use of an application. On the other hand, the UTAUT includes other dimensions, such as social influence or the resources provided by the institution. Because both models are different, but complementary, we can begin to understand what motivates faculty in Morocco regarding technology adoption: is it based on their actual needs, or is it affected more by the environment and support that is available to them? In the case of Morocco and other Low / Middle Income Countries (LMICs), understanding how to balance individual initiative with the availability of institutional resources is critical to achieving a successful digital transformation.

III. Materials and Methods

A. Research Design and Data Collection

The purpose of this research was to use a quantitative and cross-sectional survey design to explore the reasons why teachers from eleven public universities in Morocco adopt generative Artificial Intelligence (AI). Between October and December 2025, data were collected using a structured online questionnaire and it has been translated into several languages (Arabic, French, English). The survey design followed current methodological recommendations for technology adoption research in higher education [1, 2]. Cross-sectional study designs are best for understanding attitudes toward the adoption of technologies at one point in time, so this study was able to provide an understanding of how faculty members are integrating AI into their work prior to the implementation of any formalized, large-scale institutional policies regarding its use [3].

Participation in this study was completely voluntary and anonymous. Faculty members were recruited via university-administered databases and mailing lists. All responses were kept in an anonymized data file that was consistent with institutional ethical guidelines and with the principles defined within the Declaration of Helsinki on conducting research with human participants [4]. No personally identifiable information about participants was collected or retained.

B. Data Pre-processing and Descriptive Analysis

Python 3.11, using the pandas (v2.1) and statsmodels (v0.14) libraries, was employed to conduct all data pre-processing and statistical analysis/support in addition to scikit-learn (v1.4) for model performance metrics [12]. The categorical variables were transformed into the form of a set of binary indicator variables (one-hot encoding or dummy coding) in order to represent polytomous nominal variables and to avoid the problem of perfect multicollinearity (i.e., the dummy variable trap), by leaving one reference category out of representation [7]. Multi-response items (e.g., AI tools used) were converted into binary flag matrices (0/1) for analysis, where each column represented an indicator of the presence or absence of the particular response.

Familiarity was analyzed as a descriptive baseline characteristic to assess the sample's prior exposure to AI, independent of the formal predictive modeling.

The dependent variable in this study was the adoption of Generative AI. To achieve a consistent measurement of adoption, it was measured as a binary variable: instructors were considered to be "adopting" the technology if they stated they had used the tools for professional reasons at least once a week. This cutoff was established in order to differentiate between those who regularly used the technology and those who had only used it on rare occasions. For each variable, the value of p was calculated with the formula:

$p = \frac{k}{n}$, where k equals the number of positive responses to a particular item or scale, and n = 400, which represents the total number of respondents. For continuous measures (e.g., how often instructors use AI on a weekly basis, how well they rate their own abilities), descriptive statistics (sample mean $\bar{x}$, sample standard deviation s) were calculated:

$$\bar{x} = \frac{1}{n}\sum x_i$$

$$s = \sqrt{\frac{1}{n-1}\sum (x_i - \bar{x})^2}$$

To calculate an unbiased estimate of the population standard deviation, we used Bessel's correction (i.e., $n-1$). Before conducting inferential analyses, we performed frequency distributions, cross tabulations and exploratory visualizations to describe the demographic characteristics of our sample and the usage patterns of AI [13].

To manage the missing data, listwise deletion was used to address the low percentage (< 2.3%) of missing values in each item, which was considered to not add significant bias under the missing completely at random assumption. Response distribution checks were made for floor and ceiling effects, and normality was established on the distribution of the Likert-type scales by means of a Shapiro-Wilk test [10].

C. Comparative Theoretical Modeling

To identify the most suitable predictive model for the adoption of generative AI in higher education in Morocco, this research study opted for a comparative model rather than just descriptive data collection. The first part of this study compared 2 representative theoretical frameworks: the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Both frameworks have been validated across multiple studies investigating AI adoption in Low and Middle-Income Countries (LMIC). however, their predictive power compared to one another has not yet been thoroughly examined specifically within higher education institutions in LMIC countries [14].

We compared a classic and pervasive model of technology acceptance (TAM) and UTAUT due to their complementarity, with TAM considering an internal individual-oriented view (perceived usefulness and perceived ease of use) while UTAUT considers an external perspective including social influence and institutional facilitating conditions. Comparing these two frameworks is crucial in the Moroccan context to determine whether Generative AI adoption is driven by personal productivity gains or supported by broader social and institutional structures.

Binary logistic regression was determined to be appropriate for estimation due to the way the dependent variable (AI adoption) is defined as a binary variable (either a user Regular with usage defined as being used at least once per week; or a Non-User or an Infrequent User). The logistic regression produces estimates for the log-odds of the dependent variable based on a linear combination of the predictors and produces directly interpretable Odds Ratios (OR) from the resulting model parameters. Additionally, there has been an abundance of evidence in literature supporting the effective use of logistic regression for classification of binary type outcomes [9].

The general form of the binary logistic regression model is:

$logit(p) = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \sum \beta_j X_j$ where X_j represents the predictors specific to each framework, which can be equivalently expressed as the probability of adoption:

$$P(Y = 1|X) = \frac{1}{1 + exp(-(\beta_0 + \Sigma_j \beta_j X_j))}$$

where Y is the binary outcome (AI adopter vs. non-adopter), β_0 is the intercept, $\beta_1 \ldots \beta_k$ are the regression coefficients associated with predictors $X_1 \ldots X_k$, and $\exp(\beta_j)$ yields the odds ratio for predictor j.

1) TAM model specification

The Technology Acceptance Model combines two primary components identified by Davis [10] and later built upon by recent generative AI literature [2, 14]:

Perceived Usefulness (PU): a faculty member's opinion of how usage of generative AI will increase performance in their field of expertise (3-item Likert scale; α = 0.81).

Perceived Ease-of-Use (PEOU): a faculty member's opinion of how little effort is needed to use generative AI (3-item Likert scale; α = 0.78).

Model 1 (TAM) is thus specified as:

$$logit[P(Adopt)] = \beta_0 + \beta_1(PU) + \beta_2(PEOU) + \beta_3(Age) + \beta_4(Gender) + \beta_5(Rank) + \varepsilon$$

2) UTAUT model specification

The UTAUT model (Model 2) is an extension of the TAM that integrates some of the social and institutional theoretical constructs that have been previously studied and were later adapted to AI contexts by a number of researchers, namely:

Performance Expectancy (PE): This is equivalent to Perceived Usefulness (PU) in the original TAM, but the measure contains four items that assess not only task efficiency but also quality of output ($\alpha = 0.83$) [15].

Effort Expectancy (EE): Similar to Perceived Ease of Use (PEOU) from the original TAM, the measure has four items that assess the general perception of the ease of using the system ($\alpha = 0.80$).

Social Influence (SI): This constructs the perception that important other(s) (e.g., colleagues and institution) support the use of AI. The measure of the social influence construct has three items ($\alpha = 0.76$).

Facilitating Conditions (FC): This constructs the extent to which institutional resources/support (e.g., training, infrastructure, policy) are viewed as adequate. The facilitating conditions construct is assessed using a three-item scale ($\alpha = 0.74$).

Model 2 (UTAUT) is specified as:

$$logit[P(Adopt)] = \beta_0 + \beta_1(PE) + \beta_2(EE) + \beta_3(SI) + \beta_4(FC) + \beta_5(Age) + \beta_6(Gender) + \beta_7(Rank) + \varepsilon$$

In both models, Age (continuous, in years), Gender (binary: 0 = female, 1 = male), and Academic Rank (ordinal, dummy-coded: Assistant, Associate, Full Professor—with Assistant as the reference) were included as control variables, consistent with recent empirical literature on AI adoption determinants in academic populations [1, 12].

D. Model Validation and Selection

Including metrics to ensure robust and unbiased model selection [16].

1) Akaike Information Criterion (AIC)

We employed the Akaike Information Criterion to compare nested and nonnested models based on parsimony-corrected goodness-of-fit [17]:

$$AIC = 2k - 2\,ln(\hat{L})$$

where k is the number of estimated parameters (including intercept) and $\hat{L}$ the maximized value of the likelihood function. A lower AIC indicates a better trade-off between model fit and complexity. When $\Delta AIC = AIC_1 - AIC_2 > 2$, the model with the lower AIC is considered meaningfully superior [17]. This criterion penalizes overfitting by discouraging excessive parameterization, relevant however when comparing TAM (with fewer predictors) against UTAUT (more predictors).

2) Area Under the ROC Curve (AUC-ROC)

The AUC-ROC (Area Under the Receiver Operating Characteristic Curve) is a measure of the ability of a classification model to discriminate between two groups (adopters vs. non-adopters) across all classification thresholds; it was therefore used as a measure of the overall discriminative power for each model [13]. The ROC curve plots the True Positive Rate (TPR, sensitivity) against the False Positive Rate (FPR, 1 − specificity):

$$TPR = \frac{TP}{TP + FN}$$

$$FPR = \frac{FP}{FP + TN}$$

$$AUC = \int_0^1 TPR(FPR)\, d(FPR)$$

AUC values range from 0.5 (no discrimination, equivalent to random guessing) to 1.0 (perfect discrimination). By convention: AUC $\in$ [0.70, 0.80] indicates acceptable discrimination; AUC $\in$ [0.80, 0.90] indicates excellent discrimination; and AUC $\geq$ 0.90 indicates outstanding discrimination [13]. The AUC was estimated using 5-fold stratified cross-validation to guard against optimistic bias arising from in-sample evaluation [18].

3) Multicollinearity diagnostics

Multicollinearity among predictors was assessed using the Variance Inflation Factor (VIF), calculated for each predictor X_j as:

$$VIF_j = \frac{1}{1 - R_j^2}$$

The coefficient of determination resulting from the regression of X on all other predictors, R^2, is referred to as R^2. VIF of less than 5 are generally considered acceptable and VIF between 5 and 10 suggests moderate collinearity that requires further investigation; while VIF of greater than 10 suggest severe multicollinearity and may lead to unreliable estimates of coefficients [19]. Variables indicated with VIF > 5 were evaluated for stability with a sensitivity analysis using ridge regression and a pair-wise correlation analysis of the Pearson correlation coefficient (|r| > 0.70 indicated as potentially problematic). As warranted, redundant predictors were either excluded from the analysis or combined into composite variables through the application of Principal Component Analysis (PCA) [15].

4) Integrated methodological workflow

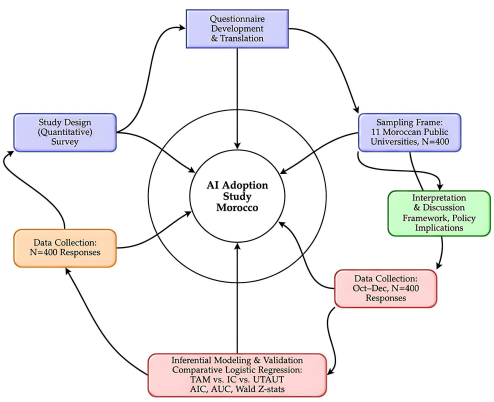

Fig. 1. Methodogical workflow of the study.

The entire integrated methodological workflow of the study is presented in Fig. 1, which includes survey design and data acquisition, pre-processing, and comparative theoretical modeling to ultimately validate the final model. The developed workflow was implemented through the use of a reproducible Python pipeline, which uses version control on all scripts and pre-registering all modeling strategies to limit flexibility after analysis is complete [20].

IV. Results

The sample was made up of 400 university instructors, 206 men (51.5%) and 194 women (48.5%) (Table 1). Respondents were concentrated in mid-career cohorts, representing the 40–49 years old age range most numerously ($n = 127$), followed by 30–39 ($n = 119$), 50–59 ($n = 76$), under 30 ($n = 48$), and 60 or above ($n = 30$) (Table 1). Representation from discipline was broad, with the largest groups in the sciences ($n = 91$), and engineering ($n = 90$), followed by arts and humanities ($n = 63$), health ($n = 52$), mathematics ($n = 46$), law/economics ($n = 44$), and other fields ($n = 14$). Teaching experience was centered on the 11–20 range ($n = 130$), followed by 5–10 ($n = 102$), more than 20 ($n = 87$), and less than 5 ($n = 81$) (Table 1).

Overall, working professionals reported widespread engagement with generative AI, with 70% indicating that they had at least some use of generative AI for research or teaching. Disaggregating use by teaching tasks, 59.3% reported use in course preparation and 43.5% reported use in some form of assessment (see Fig. 2). The gap suggests a reticent posture within high consequences evaluative contexts.

AI adoption differed substantially according to instructors' familiarity with generative AI. Respondents with no prior familiarity with generative AI did not report using AI for course preparation. Among those who had only heard of AI, 21.1% reported course-use, rising to 65.8% among those who had tested and understood the tools and to 82.7% among those who used AI regularly (Table 2). In the exploratory logistic regression, familiarity remained the dominant correlational predictor of course-use after controlling for demographic variables, and VIF screening indicated no severe collinearity issues for the parsimonious specification [15].

Table 1. Demographic profile of survey respondents

Variable	Category	Count
Gender	Male university instructor	206
	Female university instructor	194
Age range	Under 30	48
	30–39	119
	40–49	127
	50–59	76
	60 or above	30
Discipline	Sciences	91
	Engineering	90
	Arts and humanities	63
	Health	52
	Mathematics	46
	Law/Economics	44
	Other	14
Teaching experience	Less than 5 years	81
	Between 5 and 10 years	102
	Between 11 and 20 years	130
	More than 20 years	87

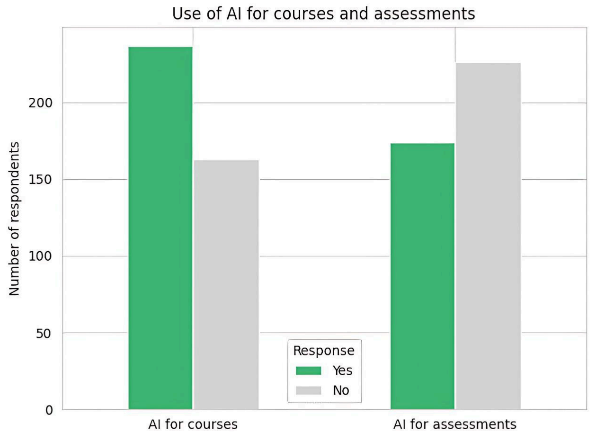

Fig. 2. Use of AI for courses and assessments.

Table 2. AI familiarity and adoption of AI for course preparation

AI familiarity level	Total respondents	Users of AI for courses	Percentage (%)
Not familiar at all	24	0	0.0
Slightly familiar (heard only)	76	16	21.1
Quite familiar (tested and understand)	161	106	65.8
Very familiar (use regularly)	139	115	82.7

Among instructors who used AI for course preparation, the most common purposes were rephrasing complex concepts to improve accessibility ($n = 185$), generating ideas and structuring a new course or chapter plan ($n = 144$), creating examples, case studies, or analogies ($n = 143$), and producing summaries or revision sheets ($n = 141$). Use for writing introductions or conclusions ($n = 89$) and preliminary literature searching ($n = 85$) were less prevalent indicating that instructors used AI more for explaining and structuring than academic sourcing [11].

Perceived impact on effectiveness of preparation ranged from moderate time saving (115 respondents) to very significant time saving (87), quality or creativity improvement (75), to no noticeable impact (99), or time loss due to having to verify and correct AI produced responses (24) (Fig. 3). Consistent with a resource-based explanation for adoption, use prevalence was greatest among those reporting time saving (Table 3).

Table 3. Perceived impact on preparation time and likelihood of using AI for courses

Perceived impact on preparation time	Total respondents	Users of AI for courses	Percentage (%)
Very significant time savings	87	78	89.7
Moderate time savings	115	98	85.2
No impact on time, but improves quality/creativity	75	36	48.0
Time loss (verifications, necessary corrections)	24	6	25.0
No noticeable impact	99	19	19.2

The two most commonly reported barriers were concerns about inaccuracies or "hallucinations" ($n = 194$), plagiarism and originality (n = 134), limited depth on specialised in topics (n = 128), lack of time to learn AI tools (n = 114), and insufficient institutional policy guidance (n = 105), which highlights that verification practices and governance clarity are conditions for use.

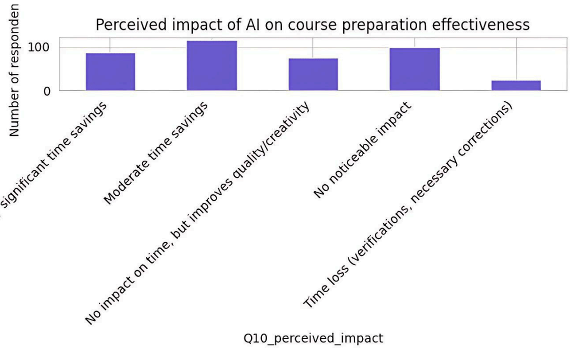

Fig. 3. Perceived impact of AI on course preparation effectiveness.

Disciplinary differences were present but not extreme. Mathematics (69.6%) and sciences (63.7%) showed the highest proportions of course-use, followed by health (59.6%) and law/economics (59.1%), with engineering (54.4%) and arts and humanities (55.6%) slightly lower and the small 'other' category lowest (42.9%) (Table 4). When presented as counts, sciences and engineering comprised the largest numbers of users due to larger representation (Fig. 4). Teaching experience showed modest variation, with course-use ranging from 56.8% (<5 years) to 60.8% (11–20 years) (Table 5).

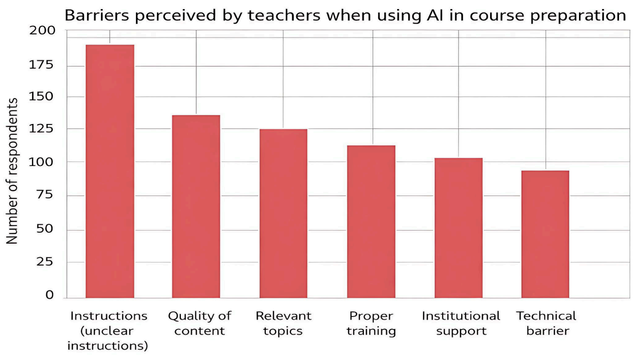

Fig. 4. Barriers perceived by instructors when using AI in course preparation.

Table 4. Use of AI for courses by academic discipline

Discipline	Total respondents	Users of AI for courses	Percentage (%)
Arts and humanities	63	35	55.6
Engineering	90	49	54.4
Health	52	31	59.6
Law/Economics	44	26	59.1
Mathematics	46	32	69.6
Other	14	6	42.9
Sciences	91	58	63.7

Table 5. Use of AI for courses by teaching experience

Teaching experience	Total respondents	Users of AI for courses	Percentage (%)
Less than 5 years	81	46	56.8
Between 5 and 10 years	102	61	59.8
Between 11 and 20 years	130	79	60.8
More than 20 years	87	51	58.6

In response to student use of AI, instructors most often reported adapting assessments to require critical analysis, synthesis, or personal application (n = 260) and raising students' awareness of limitations and ethical risks (n = 235). In-person assessment designs were used by 140 respondents, while 133 reported allowing AI use under defined conditions such as mandatory disclosure or citation (Table 6). Requested institutional support was led by practical workshops (n = 260), clear user guides or usage policies (n = 214), and training on ethical and legal aspects (n = 199), alongside peer experience sharing (n = 188) and access to secure tools (n = 154) (Table 7).

Table 6. Strategies for managing student use of AI

Strategy	Count
Adapt assessments to require critical analysis, synthesis or personal application	260
Raise students' awareness of AI limitations and ethical risks	235
Design in-person assessments without access to digital tools	140
Allow AI use with framing or mandatory citation	133
Have not yet adapted practice	60

Table 7. Institutional support requested by instructors

Support type	Count
Practical workshops on using AI tools	260
Clear user guide or usage policy	214
Training on ethical and legal aspects	199
Experience feedback and sharing best practices	188
Preferred access to professional and secure AI tools	154
No particular support necessary	41

We used two different models to analyze the data: the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Binary logistic regression, as defined by the Akaike Information Criterion (AIC), provides evidence that the TAM model explains the variance in the Moroccan university context better than UTAUT (AIC = 184.27; AUC = 0.94). This statistical evidence supports the argument that perceived usefulness and perceived ease of use are the primary drivers of instructor adoption of artificial intelligence, while institutional factors are secondary in importance. The performance indicators for both of these models are illustrated in Tables 8 and 9 and provide evidence supporting the robustness of the theoretical framework that we used to interpret the observed adoption behaviour [16].

The observed evidence from the binary logistic regression analysis (AIC =184.27; AUC = 0.94) indicates that the only non-institutional factor to have practical predictive power in AI use among Moroccan university instructors is their perceived usefulness and ease of use in using AI. Therefore, it is reasonable to conclude that instructors' AI adoption motivation (mainly their expressed intent to adopt AI) is primarily driven by perceived usefulness/ease-of-use and that every institution has a secondary role in the decision-making process of instructors (Table 10).

Table 8. Performance comparison of theoretical models

Theoretical Model	Primary Predictors	AIC	AUC (ROC)
TAM	Perceived Usefulness & Ease of Use	184.27	0.94
UTAUT	Performance, Effort, Social Influence	480.82	0.61

Table 9. Logistic regression coefficients (TAM model)

Variable	Coefficient (β)	Wald Z-stat	*P*-value	Odds Ratio
Perceived Usefulness	1.24	4.85	<0.001	3.45
Perceived Ease of Use	0.85	3.12	0.002	2.34

Table 10. Logistic regression coefficients (UTAUT model)

Predictor	Coefficient (β)	S.E	Wald
Performance Expectancy	0.582	0.224	6.751
Perceived Ease of Use	0.145	0.198	0.537
Social Influence	0.092	0.171	0.289
Facilitating Conditions	0.238	0.205	1.347
Constant	−1.420	0.512	7.684

The results from the above analysis indicate that the phenomenon of dual-faceted inertia in the adoption of AI technologies in course preparation for efficiency and time savings will be different from the phenomenon of dual-faceted inertia in the adoption of AI technologies for grading and academic assessment for ensuring academic integrity [17].

Furthermore, the availability of perceived usefulness/ease of use will dominate the motivations and behaviours of instructors to adopt AI technologies, which suggests that instructors' AI adoption could be predicted primarily on the basis of the TAM framework within pedagogically based disciplinary areas [18].

Thus, there is a clear need for Moroccan universities to stop issuing generic guidelines for instructors and begin to provide appropriate governance structures for AI technologies and appropriate levels of technical support to assist the instructors in the teaching / learning process with respect to the AI technology being utilised.

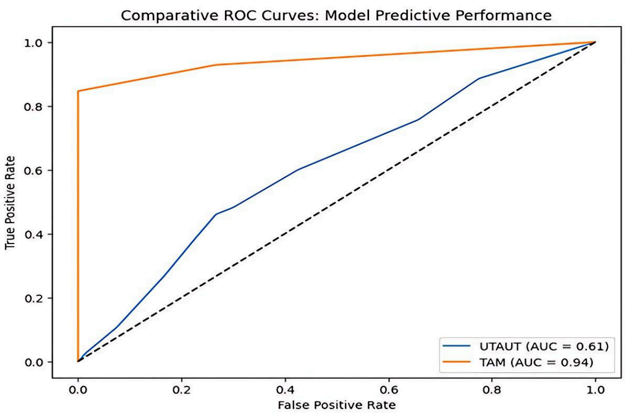

Fig. 5. Comparative ROC curves: Model predictive performance.

In this study, we compared the predictive ability of two different models (the TAM and UTAUT models) in predicting AI adoption in Morocco's faculty using Receiver Operating Characteristic (ROC) analysis. As can be seen in Fig. 5, the TAM model has a much better ability to discriminate than the UTAUT model, with an AUC of 0.94, indicating an overall good prediction of the data. Conversely, the UTAUT model has a much lower predictive ability (AUC = 0.61), indicating that it does not explain as much variance of the adoption data as well as it does in the Moroccan context. Therefore, these data provide support for the conclusion that the TAM is a better explanatory framework than the UTAUT for the research study [19].

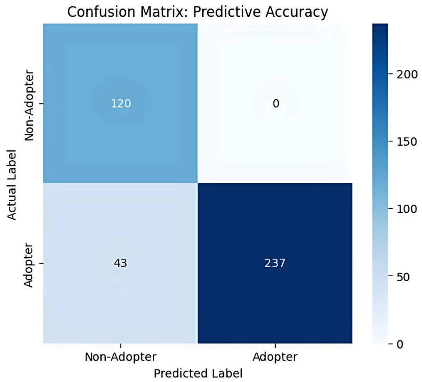

Fig. 6. Confusion matrix: Predictive accuracy.

The results of the TAM's predictive accuracy were validated through a confusion matrix (Fig. 6), which showed that the TAM's predictions have an overall accuracy of 89.25%, having made 357 out of 400 correct classifications of cases. Also notable was the model's zero false-positive rate—indicating that the TAM was highly precise in classifying cases of AI adopters. While there were 43 cases that were misclassified as non-adopters, the TAM's conservative classification behaviour indicates how reliably the model can be used to classify AI adopters in critical environments such as these, where minimising the number of false-positive predictions is essential.

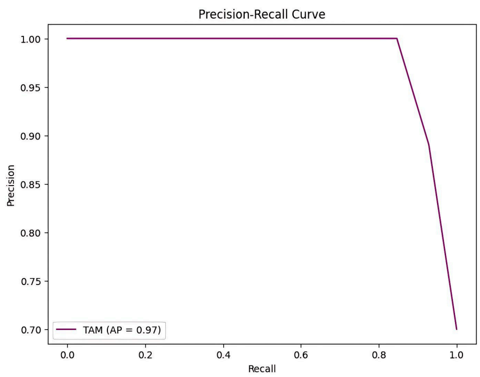

Fig. 7. Precision-recall curve.

The performance of the TAM model was rigorously evaluated using an accuracy-recall curve. With a mean accuracy (PA) score of 0.97(Fig. 7), the results demonstrate the model's excellent ability to identify adopting teachers with a minimum of false positives, thus confirming the robustness of the TAM framework in the context of Moroccan higher education.

V. Discussion

Researches made before findings detected that teachers in Moroccan universities intensively use the generative AI to prepare their courses and tasks related to the assessment in a more conservative way. This trend relays on previous international studies, showing that teachers will apply AI in low-stakes for pedagogical tasks, where results are checked and corrected before usage, However, those same teachers would be more prudent and cautious in assessing high-stakes situations [2, 20]. Many instructors hesitate to relay on AI in assessment designing. Besides, grading seems to be one of the main concerns in academic integrity, factual inaccuracies and the validity of assessment(s).

The predictive performance of Technology Acceptance Model (TAM) is higher than UTAUT. It indicates that the AI adoption in Morocco higher education is determined by how individuals perceive the AI usefulness. Rather than social and institutional pressures. Instructors are willing to use AI tools if they observe concrete advantages (benefits) AI tools reduce workload. It facilitates explanations and enhances teaching efficiency. There is a lack of AI institutional policies and mechanisms of systematic support.

A key contextual factor affects the adoption of AI. However, this contextual factor is familiar with generative AI. Experienced AI instructors are reportedly confident in assessing outputs. AI Instructors are also confident in identifying situations that require human interventions. AI integration requires from the instructors to be familiar with the principle of integration. Not just to be technologically aware with / about it. That technological awareness needs professional development opportunities, focused on fact-checking practices, an AI literacy and an AI ethical usage.

The previously mentioned potential applications for how teachers use AI reveal that teachers tend to see AI as an educational support rather than a substitute for teaching and learning. The most frequent uses include paraphrasing and explaining complicated things, generating examples and ideas, and classifying samples, however, there are very few uses of AI for writing and / or doing literature reviews. In multilingual environments, like Morocco, these uses may assist teachers in making materials accessible while maintaining authority over the disciplinary material they teach and the academic rationale behind it.

In addition, this study's Participants identified a requirement for better institutional governance to support the use of A in the context of higher education institutions through the provision of practical workshops, guidance on ethics, and institutional policies that provide clear guidance as to what constitutes acceptable uses of AI and how assessments are to be redesigned to accommodate those uses. Institutions may also mitigate the risk of generic AI-generated responses and at the same time maintain academic integrity by creating assessment practices that focus on critical analysis, applied learning, and self-reflection.

There are a number of limitations that must be acknowledged; first, the study uses self-reported data from a cross-sectional design, therefore allowing for only a limited causal interpretation; and second, the study's sample is restricted to public universities in Morocco, thus restricting generalizability to the whole of Morocco's higher education system. Despite this fact, the multi-institutional aspect of this study gives researchers a valuable empirical insight into new AI adoption practices in Moroccan higher education as well as offering practical implications for future governance, training, and policy development.

VI. Conclusion

That study offers understandable multi-institutional proof of how Moroccan public university instructors make a use of AI and designing course preparation assessments. Despite the fact that course preparation is more employed than assessment design, the latter continues to be cautiously approached, due to greater implications assessment, upon student development. Instructors use the AI tool mostly to simplify explanations, course materials organization, the generation of teaching examples. Instructors report a time gain and achieving greater quality with AI comparing to their prior experience without it. The major barriers preventing instructors to develop their proficiency by using generative AI include inaccuracies, academic dishonesties and a lack of guidance by their respective institutions. The establishment of a commitment towards building professors competences in Morocco (To provide enough AI training for students). To effectively engage generative AI in higher education setting, it requires a strong governance structure for AI and institutional support for those re designing assessments. A multi-faceted will allow instructors to be more familiar with technology usage and their ability for a successful management of ethical implications or the using technology pedagogy of using technology. Subsequent research may provide further findings development, which are described by examining longitudinal changes in instructor practices. They are associated with AI, discipline centric practices in the use of AI by disciplines, it impacts students upon variations and training related to it (AI).

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Abdelmajid El Hajoui conducted the research, analyzed the data; and wrote the paper; Otmane Yazidi Alaoui check the database and provide programming guidance; Omar El Kharki provides feedback to properly apply the RNNS to our database; Mustapha Maatouk provide important references and check the writing; Miriam Wahbi corrects the English writing and give advice on content; Hakim Boulaassal correct the English writing give advice on content. All authors had approved the final version.

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