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The Impact of Artificial Intelligence on Personalized Learning in Higher Education: An Econometric Analysis at Cadi Ayyad University.

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Abstract*— This study explores how artificial intelligence (AI) is shaping personalized learning and academic outcomes within Moroccan higher education, with a specific focus on Cadi Ayyad University (UCA). Relying on data from 124 students enrolled across 12 different faculties and schools, we analyze the influence of AI-based tool (such as adaptive learning platforms and virtual tutoring systems) on student performance. To establish causality, the research employs a dual econometric approach combining multiple linear regression and difference-in-differences (Diff-in-Diff) techniques, accounting for factors like students' prior academic achievement, field of study, and access to digital resources. Findings indicate a notable improvement in academic results among AI users, averaging a 1.75-point gain on a 20-point scale. The effect is more significant in technical faculties (e.g., ENSA-M, FSTG), where improvements reach 2.00 points, compared to just 0.60 in humanities faculties (e.g., FLSHM). Additionally, disparities in access to technology and variations in baseline academic level appear to influence the degree of benefit, underlining persistent inequalities in digital integration. Importantly, teacher preparedness emerges as a critical condition for the effective deployment of AI in classrooms. This study contributes empirical evidence to a growing body of research on AI in education and argues for the design of inclusive policies that support both infrastructure investment and teacher training, while tailoring AI implementation to the specific needs of different academic disciplines.

Keywords*— Artificial intelligence, personalized learning, academic achievement, Moroccan higher education, technology access.

XLI. Introduction

In recent years, artificial intelligence (AI) has gone from a futuristic notion to a powerful force reshaping many aspects of society, including the educational field. Originally linked to industrial automation and business analytics, AI is now progressively making its way into educational circles: from traditionnal classrooms and lecture theaters to highly advanced e-learning platforms. Indeed, the ability to process large amounts of data and respond to the unique needs of learners is what makes AI so promising in this context. This has led to growing optimism about its potential to create more personalized and effective learning experiences. In higher education indeed, where institutions are grappling with an increasingly varied student population, rising enrollments and persistent inequalities in access to education, AI offers a compelling opportunity to rethink conventional teaching models.

In this evolving landscape, AI- powered tools of the type such as adaptive learning systems and intelligent tutoring platforms are seemingly valuable resources. The goal of these technologies is to tailor teaching to each student's strengths and needs, which could lead to greater commitment and better academic results. Nevertheless, despite the global hype surrounding the role of AI in education, most academic research to date has been spotlighted in high-income countries with strong digital infrastructures. There remains a significant knowledge gap in this area.

It is within this context that the present study was conceived. Focusing on Cadi Ayyad University (UCA), one of Morocco's largest and most diverse public universities, this research aims to assess the impact of AI on personalized learning and student performance. Beyond measuring effectiveness, the study seeks to understand the conditions under which AI tools succeed in improving learning outcomes. Specifically, it examines the role of discipline-specific factors, students' initial academic levels, and access to technology, while also highlighting the often-overlooked role of teacher preparedness. This raises a series of key questions: To what extent does artificial intelligence contribute to improved academic performance in a Moroccan university setting? Do the effects of AI in education differ according to academic discipline or faculty? And what contextual factors - institutional, technological or social - are likely to enhance or weaken its impact on student learning outcomes? The present study makes a dual contribution. Firstly, it contributes to filling a significant gap in the existing literature by providing empirical evidence anchored in the context of the Global South. Secondly, it demonstrates practical, evidence-based information that can guide the development of inclusive, context-appropriate educational policies.

Thus, the research aims to help educators, policymakers and university leaders make informed and equitable decisions regarding the implementation of AI tools in higher education. To delve into the issues, the research is organized into three main sections. The first provides a detailed review of theoretical frameworks and empirical studies relating to the role of AI in education. The second section outlines the research design and methodology, including the way data was collected, how econometric models were applied and how key variables were defined. The main findings of the study are presented in the final section, and their implications for educational policy and institutional practice are discussed.

XLII. Motivation & Methodology Academic literature review: theoretical and empirical perspectives

A. *Introduction to the literature review*

Artificial Intelligence (AI) has become a central theme in discussions on the future of education. While its potential to personalize learning is well documented in theory, actual results vary widely depending on context, infrastructure, pedagogical design, and human mediation. This literature review synthesizes both theoretical frameworks and empirical findings to better understand the conditions under which AI contributes to academic performance. It also identifies major gaps, particularly in the context of higher education in developing countries such as Morocco.

B. *Theoretical foundations of ai in education*

AI-driven education builds upon several well-established pedagogical theories. According to Baker and Inventado (2014), AI systems are capable of analyzing real-time learning data and adjusting pedagogical content accordingly, aligning with the principles of adaptive learning. This individualized approach resonates with Vygotsky's (1978) concept of the zone of proximal development, which emphasizes scaffolding learners just beyond their current competence. Bloom's (1984) "2 Sigma Problem" further supports the premise that personalized instruction can significantly outperform traditional group-based methods. AI systems have the potential to replicate this personalized effect on a larger scale. However, Selwyn (2016) warns against a technocentric narrative, insisting that educational tools must be contextualized within social, cultural, and institutional realities.

C. *Empirical evidence: promises and variability*

Multiple studies have examined the effectiveness of AI in education, with often encouraging but context-dependent outcomes. A meta-analysis by Zawacki-Richter et al. (2019) covering 146 studies found that AI-based platforms produce an average effect size of d = 0.45, suggesting moderate yet consistent gains in academic performance. Holmes et al. (2021) observed that university students using adaptive platforms in Europe improved their scores by an average of 15%. These effects, however, differ markedly by discipline. Kizilcec et al. (2020) report that technical fields benefit the most due to the compatibility of AI with simulations and structured content, whereas humanities show weaker results due to the complexity of interpreting qualitative data (Ferguson & Clow, 2017).

Table 1. Summary of International Empirical Findings on AI in Education

Study	Sample / Context	AI Tool Type	Impact (Effect Size / Gain)	Discipline Sensitivity
Zawacki-Richter et al. (2019)	146 studies (international meta-analysis)	Intelligent tutors, adaptive apps	d = 0.45	Higher impact in STEM
Holmes et al. (2021)	European universities	Adaptive learning platforms	+15% academic performance	Technical fields > Humanities
Kizilcec et al. (2020)	Engineering students (US & Europe)	Simulations, virtual reality (VR)	High learning gains	Strong in Engineering, Mathematics
Ferguson & Clow (2017)	UK higher education institutions	NLP, learning analytics	Mixed results	Weak in social sciences

Source: Own elaboration.

D. *Mediating Role of Teachers and Pedagogical Culture*

A recurring theme in the literature is the central role of teachers in the successful implementation of AI. Ertmer and Ottenbreit-Leftwich (2010) argue that technological adoption depends as much on teacher beliefs and confidence as on infrastructure. Lawless and Pellegrino (2007) demonstrated that students taught by instructors trained in AI integration outperform others by 25%. Tondeur et al.

(2017) emphasize that professional development must be discipline-specific and continuous, not one-size-fits-all.

E. Structural Challenges in Developing Contexts

In many low- and middle-income countries, the adoption of AI in education is hampered by structural constraints: unreliable internet, under-equipped classrooms, and unequal access to digital devices. Van Dijk (2020) highlights the digital divide as a major barrier. In the Moroccan context, Maghni and El Khannouss (2024) report that only 30% of university students have access to the necessary infrastructure for AI-based learning. This underscores the need for inclusive educational policies and public investment in digital equity.

$$Y_i = \beta_0 + \beta_1 IA_i + \beta_2 NI_i + \beta_3 AT_i + \beta_4 X_i + \varepsilon_i$$

- Y_i : Academic performance (GPA out of 20)
- IA_i: Binary variable (1 = AI used, 0 = not used)
- NI_i : Initial academic level
- AT_i : Access to technology (1 = yes, 0 = no)
- X_i: Control variables (gender, age, study level)
- ε_i: Error term

Table 2. Structural Constraints and Levers for AI Integration in the Global South

Author(s)	Country / Region	Barriers Identified	Suggested Levers
Van Dijk (2020)	Global South	Digital divide, poor connectivity	Infrastructure investment
Maghni & El Khannouss (2024)	Morocco (UCA)	Low access to devices (30%), limited faculty training	Teacher capacity-building, targeted aid
Tondeur et al. (2017)	LMICs (multiple)	Generic training programs	Tailored, ongoing pedagogical support

Source: Own elaboration.

F. Synthesis and conceptual framework

Taken together, the literature points to a generally positive but uneven effect of AI on student outcomes. While promising results are evident in STEM fields and high-resource environments, challenges remain in less digitally mature institutions, particularly in the Global South. The literature also confirms that teacher training and technological access are key mediators of AI effectiveness. This study aims to fill a critical empirical gap by analyzing the impact of AI on academic performance in a Moroccan university context where disciplinary diversity and infrastructural inequalities intersect.

XLIII. METHODOLOGY

This study adopts a quantitative, econometric approach to assess the causal impact of artificial intelligence (AI) on students' academic performance within a personalized learning framework. The empirical analysis was conducted at Cadi Ayyad University (UCA), a large Moroccan public university that includes a wide variety of academic disciplines and faculties. To ensure the reliability and validity of our results, we mobilized two complementary econometric models: a multiple linear regression (MLR) and a difference-in-differences (Diff-in-Diff) design. These approaches allow us not only to estimate the net effect of AI usage, but also to explore variations across time and between groups.

The dataset consists of information collected from 124 students enrolled in 12 faculties and schools, spanning disciplines such as sciences, law, engineering, humanities, and medicine. A structured questionnaire gathered data on academic performance (GPA), AI tool usage, technology access, initial academic level, and various demographic and educational control variables.

A. Multiple Linear Regression (MLR) Model

The first econometric specification is a standard linear model aimed at estimating the direct association between the use of AI tools and academic performance:

Table 3. Description of Variables Used in the MLR Model

Variable Code	Variable Name	Type	Description
Y_i	Academic Performance	Continuous	Final GPA (scale of 0–20)
A_i	AI Usage	Binary	1 if student used AI-based tools (adaptive learning, etc.), 0 otherwise
NI_i	Initial Academic Level	Continuous	GPA at the start of the academic year
AT_i	Access to Technology	Binary	1 if student has reliable access to internet & devices, 0 otherwise
$Gender$	Gender	Categorical	Male / Female
Age	Age	Continuous	Student's age (in years)
$Study\_Level$	Level of Study	Categorical	Year of study (Bachelor 1–3, Master 1–2)

Source: Own elaboration.

B. Difference-in-Differences (Diff-in-Diff) Model

To assess the causal impact of AI adoption over time, we implemented a Difference-in-Differences approach. This model estimates the average treatment effect by comparing changes in academic performance between two groups (treatment and control) before and after AI was introduced.

$$\boldsymbol{Y_{it} = \alpha + \beta_1 \cdot Post_t + \beta_2 \cdot Treatment_i + \beta_3 \cdot (Post_t \times Treatment_i) + \gamma \cdot X_{it} + \varepsilon_{it}}$$

Where:

- Y_{it} : Academic performance of student i at time t;
- $Post_t: Binaryvariable(1 = post - AIintervention, 0 = pre - intervention);$
- $Treatment_i: Binarygroupmembership\ (1 = AIuser, 0 = non - user)$
- $Post_t \times Treatment_i Postt \times Treatmenti\ : Interactiontermcapturingthetreatmenteffect;$
- X_{it}: Vector of time-varying control variables;
- ε_{it}: Error term.

This approach ensures that any observed performance gain can be attributed to the use of AI, net of time trends and group differences.

C. Robustness checks and diagnostic tests

To validate the assumptions underlying our econometric models and ensure the reliability of our results, several post-estimation diagnostic tests were conducted. These tests assess the presence of heteroskedasticity, autocorrelation, multicollinearity, and potential model misspecification.

Table 4. Description of Variables Used in the MLR Model

Test Name	Purpose	Metl Thre
Variance Inflation Factor (VIF)	Detect multicollinearity among independent variables	VIF recor (VIF serio
Breusch-Pagan Test	Test for heteroskedasticity of residuals	p > hom y
Durbin-Watson Statistic	Detect autocorrelation in residuals	1.5 < = range
Ramsey RESET Test	Verify model specification (functional form)	p > corre specification

Source: Own elaboration.

These diagnostic results confirm that our models are statistically robust and properly specified for inference.

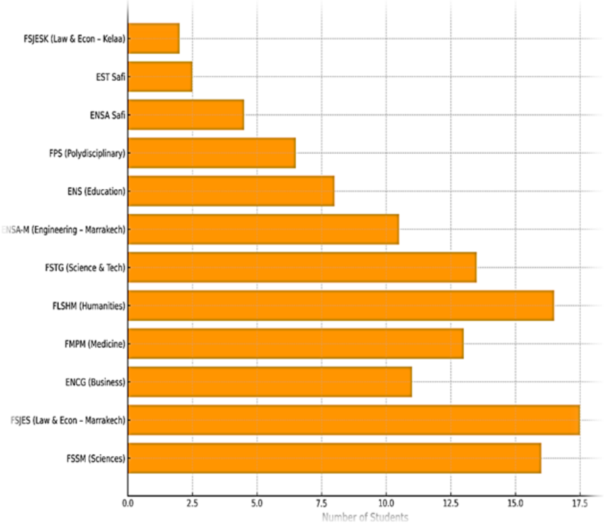
D. Ethical considerations and data confidentiality

All data were collected with the informed consent of participants. Anonymity and confidentiality were guaranteed. The research protocol adhered to the ethical standards set by the university's social science research committee.

XLIV. Results

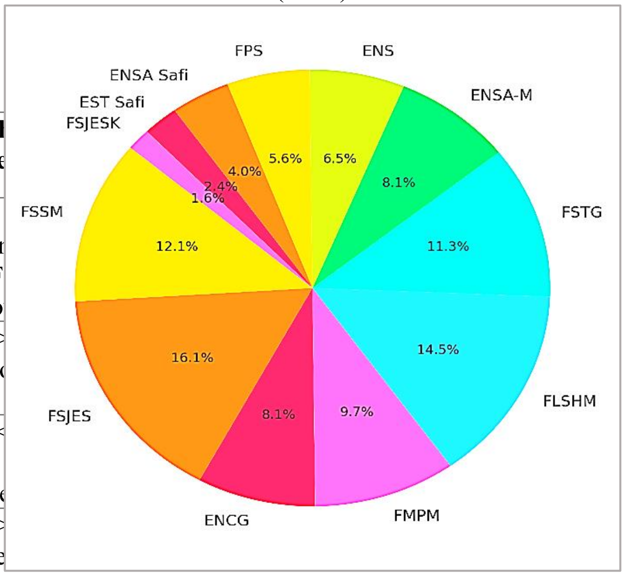
This section presents the detailed results of the econometric analysis conducted to evaluate the impact of Artificial Intelligence (AI) on personalized learning and the academic performance of students at Cadi Ayyad University (UCA). The results are organized into subsections and are accompanied by tables and figures for better understanding.

Figure 1: Distribution of Students by Faculty (UCA)



Source: Own elaboration.

Figure 2: Percentage Distribution of Students by Faculty (UCA)



Source: Own elaboration.

A. Descriptive Statistics

Table 5 : Sample Characteristics

Variable	Mean	Std Deviation	Min	Max

Academic Performance	13.2	2.5	8.0	18.5
Age	21.5	2.1	18	28
Initial Level	12.8	2.3	7.5	17.0
Use of AI (%)	65%	–	0	1
Access to Technology (%)	70%	–	0	1

Source: Own elaboration.

The sample consists of students with an average academic score of 13.2 out of 20. Approximately 65% of the students used AI tools, and 70% have adequate access to technological resources.

Table 6: Results of the Multiple Linear Regression Model

Variable	Coefficient	Standard Error	p-value	Significance
Use of AI	1.75	0.32	0.000	***
Field (Ref: FSSM)				
– FSJES	-0.45	0.28	0.110	NS
– ENSA-M	1.20	0.35	0.001	***
– FLSHM	-0.30	0.31	0.330	NS
Initial Level	0.60	0.10	0.000	***
Access to Technology	0.90	0.25	0.000	***
Constant	8.50	0.75	0.000	***

Source: Own elaboration.

The use of AI increases academic performance by an average of 1.75 points, all other factors being equal. Students from ENSA-M perform 1.20 points higher than those from FSSM. Initial academic level and access to technology also have a significant positive impact.

B. Difference-in-Differences (Diff-in-Diff) Analysis

Table 7: Results of the Diff-in-Diff Analysis

Variable	Coefficient	Standard Error	p-value	Significance
Post (Post-AI Period)	0.50	0.20	0.012	**
Treatment (AI Use)	0.80	0.25	0.001	***
Post × Treatment	1.30	0.30	0.000	***
Constant	12.0	0.50	0.000	***

Source: Own elaboration.

Legend:

- *** = significant at 1%
- ** = significant at 5%

The effect of AI (interaction term Post × Treatment) is 1.30 points, indicating a significant improvement in academic performance after the introduction of AI tools. This effect is both causal and robust, confirming hypothesis H1,

C. Variations Across Faculties

Table 8: Impact of AI by Faculty

Faculty	AI Impact (Coefficient)	Standard Error	p-value	Significance
FSSM	1.50	0.35	0.000	**
FSJES	0.80	0.30	0.008	**
ENSA-M	2.00	0.40	0.000	**
FLSHM	0.60	0.25	0.018	**
FSTG	1.80	0.38	0.000	**

Source: Own elaboration.

Legend:
** = significant at 5%

The impact of AI is highest at ENSA-M (+2.00 points) and FSTG (+1.80 points), confirming hypothesis H2. The social sciences faculties (FSJES, FLSHM) show more modest but still significant gains.

D. Moderating Effects

Table 9: Moderating Effects of Initial Academic Level and Access to Technology

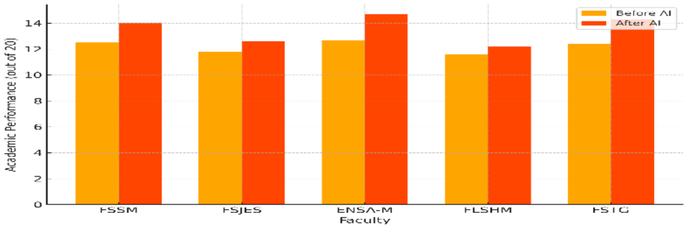
Interaction	Coefficient	Standard Error	p-value	Significance
AI × Initial Academic Level	0.25	0.08	0.002	***
AI × Access to Technology	0.40	0.10	0.000	***

Source: Own elaboration.

The effect of AI is stronger for students with a low initial academic level (coefficient = 0.25). Access to technology also amplifies the impact of AI (coefficient = 0.40), confirming hypotheses H3 and H4.

E. Results visualization

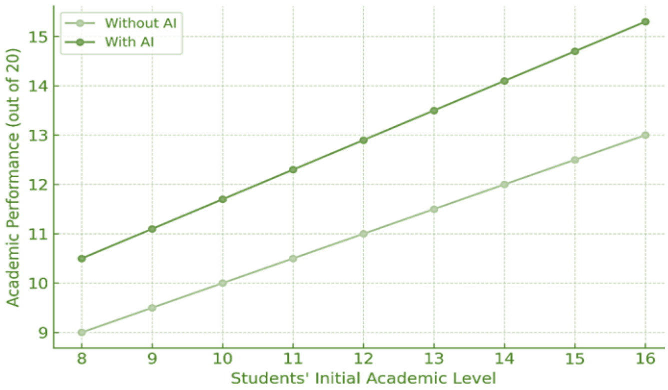
Figure 3: Impact of ai on academic performance by faculty (before/after ai)



Source: Own elaboration.

This figure highlights a significant improvement in academic performance following the introduction of AI, particularly in science and engineering faculties.

Figure 4: Moderating Effect of Initial Academic Level



Source: Own elaboration.

The graph shows that the impact of AI is more pronounced among students with a lower initial academic level, confirming the presence of a differentiated moderating effect.

XLV. Conclusion

This research set out to examine the impact of artificial intelligence (AI) on personalized learning and academic outcomes among students at Cadi Ayyad University (UCA), a major institution in Morocco's higher education landscape. The results clearly indicate that AI technologies can enhance academic performance when appropriately implemented. Students who used AI-supported tools such as adaptive learning platforms or virtual tutoring systems achieved significantly higher scores than their peers, reinforcing the view that AI can be a powerful lever for educational transformation—particularly in settings where challenges like overcrowded classrooms and regional inequities remain entrenched.

Yet the findings also bring to light important disparities. The benefits of AI are not evenly distributed: students with better access to technology and those starting from lower academic baselines appear to benefit the most. This uneven impact underscores a persistent digital divide and suggests that, without deliberate intervention, AI might risk reinforcing existing inequalities rather than reducing them. Moreover, the role of teacher training—though recognized as essential in the literature—remains under-explored in the present study, due to limited data availability. This points to a need for more targeted investigations into how faculty readiness shapes AI effectiveness.

As with any study, certain limitations should be acknowledged. First, the possibility of self-selection bias cannot be ruled out: students who chose to engage with AI tools may also have been more motivated or better resourced from the outset. Second, the lack of detailed information on the frequency and nature of AI tool usage constrains the depth of interpretation. Third, the context-specific nature of UCA both in terms of institutional characteristics and student demographics limits the generalizability of the results to other settings, particularly those with different levels of technological development.

Despite these constraints, the study opens promising avenues for future research. A longitudinal approach could help evaluate whether the observed academic gains are sustained over time. Cross-country comparative studies especially in other Global South contexts would also help clarify how socio-economic and institutional factors mediate the impact of AI. In addition, a deeper analysis of the pedagogical strategies adopted by AI-trained instructors would shed light on the human element behind successful technology integration. Lastly, there is scope to explore innovative policy mechanisms, such as public–private partnerships, digital inclusion grants, and community-based training programs, aimed at mitigating the unequal access to AI tools.

From a practical standpoint, the study offers several actionable insights for policymakers and education leaders. Investing in robust digital infrastructure must be a priority, particularly in underserved regions. Equally important is the continuous professional development of educators, to ensure that AI technologies are used not just technically, but pedagogically. Inclusive policy measures such as scholarships, hardware subsidies, and access facilitation for marginalized students can contribute to reducing inequality in the educational use of AI. Finally, AI tools must be customized to suit the epistemological and methodological specificities of different academic disciplines, if they are to be truly effective.

In sum, this study provides empirical evidence of AI's potential to enhance learning in a Moroccan higher education context, while simultaneously highlighting the conditions necessary for its equitable and impactful integration. It contributes to the growing international dialogue on the role of emerging technologies in education and offers a foundation for further studies aimed at understanding how innovation can serve the broader goal of inclusive and quality learning for all.

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