

Bridging the Digital Divide: A Predictive Analysis of AI Literacy and Educational Equity in Jordan

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Abstract

This Research aims to investigate the factors changing Artificial Intelligence (AI) Literacy and digital equity for students in Jordan, highlighting key factors allied in the Jordan Economic Modernization Vision 2033. A detailed quantitative analysis of a large-scale data set involving demographic and institutional factors in all public, private and refugee camp schools was used. Key predictors were acclaimed using enhanced statistical methodologies, such as multilevel linear modeling as well as Random Forest machine learning algorithms performed in R software. The two major enablers of AI literacy found were doorway to digital infrastructure and targeted teacher training. Introduction of structured pedagogical interventions – a very significant effect on the termination of the gender and socioeconomic digital divide in remote territory. This research will outcome in the continuation of the ministry of education's (MoE) digital transformation policies based on fallout data, facts and figures to offer it with actionable recommendations for impartial integration of AI across Jordanian educational ecosystems for complete future learning at the national level.

Keywords: Artificial Intelligence in Education; Digital Divide; Jordan; Educational Equity; Machine Learning in R; Educational Data Mining.

1. Introduction

Artificial Intelligence (AI) holds immense apparent for revolutionizing educational environments and providing approaches to teaching innovation and personalized learning (Holmes, Bialik, & Fadel, 2019; Luckin, 2018). There are, however, probable to be some side effects of this technological paradigm shift that will make existing educational disparities worse. As machine learning is more normally adopted, and tools and techniques for generative AI become more widely used, there is a growing focus on building critical skills to successfully manage and utilize these systems, referred to as AI literacy (Long & Magerko, 2020; Ayanwale et al., 2024). There is a risk of authorizing a new and more extreme "AI divide" evolve that systematically marginalizes vulnerable groups of students (Kasneci et al., 2023; Warschauer & Matuchniak, 2010).

In Hashemite Kingdom of Jordan this is a national emergency. Human capital development and digital equity have been well defined as one of the pillars of socioeconomic expansion that is sustainable (Jordan Economic Modernisation Vision, 2023; Ministry of Education, Jordan, 2023). Nonetheless, the evidence suggests that the digital infrastructure, as well as the gameness of the educational systems, differs significantly between geographic areas, learning levels and socioeconomic status (World Bank, 2024; Department of Statistics, Jordan, 2024). A variety of historical research has been conducted on the gender gap (Abu-Shanab & Al-Jamal, 2015; Sweidan & Areiqat, 2021), and on socioeconomic gaps, in which it has been known that new technologies may have a negative impact on persisting social inequalities, especially in refugee camps and rural areas where the impression can be almost imperceptible (Ma, Vachon, & Cheng, 2019; Cotella & Aburamadan, 2025).

Such inequalities are far-reaching and cannot be just described, but also - analyzed and discussed to an evident extent. Similarly, in a colossal dataset with multiple dimensions, educational data mining requires very powerful mining algorithms to link to subtle non-linear signs if it is trying to discover whether a student is successful or failing. Hence, the aim of this study is to pilot an empirical analysis of how Jordanian students are influenced regarding AI literacy and what might affect it. This study seeks to surpass this clean correlation and utilizes a newer generation of computational techniques (multilevel modeling approaches and machine learning algorithms) within the R software environment. It presents robust actionable and predictive evidence to help policymakers and educational leaders and decisionmakers build equity and context-appropriate AI integration frameworks in support of Jordan's national development program.

2. Literature Review

2.1. Theoretical Foundations of Digital Capital and Educational Equity

However, it is crucial to note that one-dimensional notions of technology access fail to obtain this digital divide in the modern context of learning and teaching, hence a sociological approach is used to investigate the issue. Social mobility and educational achievement are the 'forms of capital' (Bourdieu and Richardson 1986) which are three resources: economic, cultural and social capital. Musoba and Baez (2009) extended this framework to elucidate what can happen when cultural and social capital is turned into learning opportunities through 'economies of translation' in which privileged groups are assembling their own and new technological resources. Today, in the digital era, it is manifested in the triangular relationship between access to technology, digital literacy and the social network that is used to enable the productive use of technology, which the researchers named 'digital capital' (Warschauer & Matuchniak, 2010). The inadequate distribution of digital capital has broad and multiple repercussions. The term "Matthew effect" was coined by Stanovich (2009) to define the reading skill acquisition of students who have a starting advantage in reading and continue to learn more through further reading practice and exposure, while those who have difficulty learning to read continue to fall behind. This phenomenon is intensified when it comes to AI education, where students with high levels of digital literacy and access to AI tools can acquire increasingly sophisticated skills, while those who are disenfranchised and lack access are challenged with a host of disadvantages (Ma, Vachon, and Cheng, 2019). These situations can create a vicious circle of inequality, the breaking of which is hard to achieve by conventional education systems.

Warschauer and Matuchniak (2010) argued that the thought of fairness in EdTech can be operationalized in three related dimensions: access (inclusion and connectedness with technology); use (quantity and quality of technology use); and outcomes (impacts of technology use on learning and achievement). This three-prong approach is a good fit with the moving digital landscape in which Jordan operates today, and the inequalities in infrastructure and pedagogies as well as in learning outcomes for different demographic groups. This label has newly developed to include "critical digital literacy" "the ability to assess, analyse and responsibly and morally appoint with digital technologies" which is required for meaningful AI literacy (Hadad, Watted, & Blau, 2023).

2.2. Global and Regional Perspectives on AI in Education: Promises, Challenges, and Pedagogical Realities

Artificial Intelligence (AI) is long known for its potential to transform education by empowering the personalized learning of huge numbers of learners, freeing teachers from paperwork, and facilitating real-time feedback for learners

and educators (Holmes et al., 2019; Luckin, 2018). The possibility of autonomous systems that can acclimatize to students' learning styles, identify knowledge gaps and suggestion remedial support is very appealing from a theoretical perspective, a feat that necessitates time and resources from human teachers that can't be continuously performed (Popenici & Kerr, 2017). Yet, the reality behind the claims is more complicated: systematic reviews of AI in higher education indicate that teachers might not be used to occupied with AI technologies and that institutional settings do not always make it possible to implement AI in an equitable way (Zawacki-Richter et al., 2019).

This conversation has gained a lot of footing in the era of Generative AI, particularly in the case of large language models like ChatGPT - with amazing opportunities and challenges along the way. Generative AI allows for constructing content, learning languages, and creative problem-solving (Kasneci et al., 2023; Mollick & Mollick, 2023), whereas, on the other hand, it states a considerable challenge to crafting distinctive, tailored, and distinctive communication. Meanwhile, there are challenging questions raised regarding academic honesty, the nature of authorship, and the purposes of education in the age of machines that can generate a comprehensive spectrum of text, code and analysis (Jensen et al., 2025; Watson, 2025). Like Mollick (2024) states, 'Co-intelligence' is a new era, one where the ability to work near an AI system is a new skill and where the means of teaching and assessing will need to be restructured.

AI literacy, the competencies required to appreciate and to properly and responsibly engage with AI systems, has become no longer a luxury, and must be at the forefront of what students need to learn to supply to the future work force and civic life (Long & Magerko, 2020). But many bits and pieces of study signal that not enough students or teachers know about AI. According to Mühling and Große-Bölting (2023), novices have misconceptions about machine learning and Ayanwale et al. (2024) indicated lack of AI-literacy which is a problem in producing the next generation, among the pre-service teachers. The findings highlight the critical importance of comprehensive AI literacy initiatives that should not only impart technical skills but also train students with the right mindset to critically engage with AI.

Within the MENA context, educators are now attuned to the digital infrastructure and AI readiness (Fakih et al., 2025). The findings of the various research conducted in separate countries suggest that under the absence of AI learning materials and methods, the risk is that AI will widen the inequality gap in education. Hamlin, Adigun, and Adams (2023) have demonstrated that technology cannot compensate for structural inequalities in rural school districts, Hamouda et al. (2025) have found the same in African school systems, and Lin and Jiang (2025), along with Giray et al. (2024) and Wu et al. (2026), have revealed similar findings in the Asian education system. In addition, every field of education like music and language etc., shows a need to take AI perspectives to specific domain to increase AI literacy like Mazlan et al., (2026) and Liang et al., (2023).

2.3. The Jordanian Context: Navigating Vulnerability, Building Resilience, and Pursuing Equity

The Digital Divide in Jordan is well monitored in the last ten years as an ongoing problem. Abu-Shanab and Al-Jamal (2015) examined the gender digital divide and found that, despite that, although there is a diminution in the width of the gap, there are still significant differences in the quality and uses of technology by male and female learners. Sweidan and Areiqat (2021) highlighted the constant effects of these divides on the quality of education received in Jordanian private universities, and these disadvantages are further worsened when it comes to technology-rich

learning. Recently, a study by Hadad, Watted, and Blau (2023) travelled the influence of cultural background on digital literacy and revealed that there is significant mismatch between students' self-perceived digital competence and their actual proficiency in digital literacy, which can have costs for confidence and interactions with digital technology for learning.

Such divisions have been further highlighted and widened in the post-pandemic world. For students in higher education, Maatuk et al. (2026) appraised the effect of online learning approaches on students with various characteristics and found that the e-learning divide is not only about admittance, but also about pedagogical approaches to e-learning, home learning conditions, and institutional support. The psychological dimension of this gap was explored by Ranjan and Mukherjee (2026) who studied the consequence of cognitive dissonance on loyalty towards sick designed online education platforms such as courses in emerging regions and found that a negative experience with a sick designed platform may disturb student engagement and trust in online education in these regions.

Pivotal, however, is the fact that there are several degrees of digital and AI literacy challenges that vulnerable groups in Jordan endure. The environment of Syrian children and youth in camps like Al Baqa' is diverse and challenging, as they are stuck by the lack of infrastructure, trauma, and socioeconomic instability, all of which hinder the adoption of educational technology (UNHCR, 2024). Cotella and Aburamadan (2025) known the barricades in community engagement in Al Baqa' refugee camp, and the potential of digital technologies to offer lifelines to community engagement, as well as the need for culturally sensitive and contextually appropriate interventions to achieve community engagement. Reinprecht et al. (2021) travelled opportunities and challenges of providing online and blended learning for Syrian refugees in Jordan and Lebanon and highlighted the need to endure investing in teacher training and technical assistance to avoid a 'lost generation' of refugee children and young people.

For this, there is need to act on various aspects considering international best practices and local context. Ramaila, Dhurumraj and Iraqui (2025) presented theoretical perspectives on how to address designing an equitable and sustainable curriculum in the aftermath of the pandemic in Jordan, which involves flexibility, inclusivity and sensitivity. Reliable AI systems, with a hub on transparency, accountability, and human oversight (Ma et al., 2025), as well as international guidelines such as UNESCO's guidance for consuming generative AI in education (2023) and Holmes and Miao's recommendations for ethical addition of AI in education (2023), should be paired with effective interventions.

But technological responses need to be compensated with a perception of their limitations and potential unintended consequences. More specifically, generative AI proffers a vast economic opportunity as a new productivity frontier, and Chui et al. (2023) noted that realizing this opportunity will require significant investments in human and physical capital and institutions. According to the analysis of Ma, Vachon and Cheng (2019), other factors that need to be considered in digital equity besides education and research and development and national pay include political freedom, making the efforts to reduce the AI divide in Jordan not only educationally, but economically and politically. Finally, Selwyn (2025) points out a counternarrative and the need for a 'digital degrowth' mindset that questions the future of digital and technological 'solutionism' (a term used to describe the false promise that technology can solve complex social and educational problems). This perspective is particularly appropriate in resource-limited

environments, like in Jordan, where trade-offs, priorities, and even the core functions of 21st-century education and AI in relation to sustainability and equity must be considered.

3. Methodology

3.1. Research Design and Epistemological Framework

The methodology for this study is quantitative and predictive modeling based on a post-positivist epistemological framework which distinguishes the complexity of educational phenomena and tries to look for measurable patterns or relationships (Creswell & Creswell, 2018). A grounded theory (Charmaz, 2014) and a thematic analysis (Braun & Clarke, 2006) informed research design is used to excellent the variables, and to maintain the analysis framework flexible with acknowledge to the reality of Jordanian education. The methodological approach is in line with the recommendations of the recent literature in the field of education and emerging economies, which emphasizes the need for methodologically rigorous and contextually relevant educational research (López-Meneses et al., 2025; Ali et al., 2025).

One can justify the selection of the predictive approach to modeling, as matched to the traditional explanatory approaches, for methodological reasons. First, traditional regression-based data analysis approaches may fail to reveal important non-linear relationships and interaction effects in an involved multi-layered system, which are critical in educational data mining. Secondly, it is policy oriented, and the emphasis is on discernments that can be acted upon when making groups on resource allocation and intervention design, as well as prediction outcomes (Chui et al., 2023). Third, machine learning techniques are supplemented with traditional statistical analysis methods, which provides a comprehensive and triangulated analytical approach, further inspirational its explanatory and usefulness value (Ali et al., 2025).

3.2. Data Sources and Sampling Strategy

A wealth of data is used to account for disparity in the Jordanian educational landscape in terms of demographic, geographic and institutional variation. Data parameters were selected from the Department of Statistics' statistical data, the Annual Education Statistical Report 2023/2024 (Ministry of Education, Jordan, 2024), and the AI Integration Survey Report: Public vs. Private Schools (Ministry of Education, Jordan, 2024). The information stipulated by these sources signifies nationwide typical data regarding enrolments, infrastructure, teacher qualifications and student performance at all governorates.

A multi-stage stratified sampling strategy was used to provide adequate representation of key subpopulations. Schools were stratified according to geographic region (Amman, Rural, Refugee Camp) and school type (Public, Private) in the first stage, based on the areas of the Jordanian digital divide that have been known in the previous studies (Abu-Shanab & Al-Jamal, 2015; Sweidan & Areiqat, 2021). Random sampling without replacement within each stratum was used in the second stage to draw sample schools with the probability proportional to the size of the enrolment. In the final step, students were randomly chosen from participating schools, representing all grade levels and

demographic groups. This ends in a sample of ~1000 students, which is sufficiently large for multilevel modeling and machine learning applications, but also feasible given resource constraints.

The coverage of refugees on camp sites is an intentional methodological decision that hopefully will fill a great need in literature. Some have explored digital access for Syrian refugees in Jordan (Cotella & Aburamadan, 2025; Reinprecht et al., 2021; UNHCR, 2024), but there are a few systematic studies that have investigated AI literacy in these settings. This research is original for depicting the refugee camp schools as a separate stratum, offering new visions into the double vulnerability of the populations and its associations for designing targeted interventions.

3.3. Variable Operationalization and Measurement

To measure the dependent variable, students' empathy for AI concepts, students' assessment of AI-generated content, and students' ethical reasoning about AI applications, a legalized instrument that is continuously operationalized (0–100) (AI Literacy Score) was used. The instrument was varied from the existing instruments of AI literacy (Long & Magerko, 2020; Ayanwale et al., 2024) and cognitively interviewed with several student cohorts for adapting it to the Jordanian learning context. The internal consistency was established using Cronbach's alpha with an acceptable result of 0.87.

Independent variables are operationalized as follows: Digital Access Score (continuous 0-100) is operationalized as a measure of the availability and quality of digital infrastructure, which includes device access, internet connectivity and software availability, and is based on student self-report and validated alongside the school level infrastructure audit. Gender was treated as a binary variable (Male/Female) and this was done acknowledging the limitations of treating gender as a binary and reflecting the practiced in Jordanian educational statistics. Socioeconomic Status (SES) was operationalized as an ordinal (Low, Middle, High) synthesis of parental education, home income, and occupational status, as per the methodology of measuring SES in educational research (Ma et al., 2019). Teacher Training was operationalized as a binary variable with 'Yes' (the teacher had formal training in adding AI in the past academic year) and 'No' (no formal training).

Contextual variables were Region (Amman, Rural, Refugee Camp) and School Type (Public, Private), reflecting levels of structure which affect the nature of schooling in Jordan. When guessing the impact of these variables, they were included as fixed effects in regression models and as accidental properties in multilevel models which took account of clustering by region and by school.

3.4. Analytical Procedures and Statistical Modeling

The data was processed and analyzed with R software (version 4.3.1), and a detailed data analysis pipeline was used to gain the best possible explanatory and predictive power. The pipeline comprised four consecutive phases:

Descriptive statistics and crosstabs were performed first to decide the sample and identify initial trends of AI literacy by demographic and contextual groups. In this stage data was handled and tables were generated with packages dplyr and knitr for transparency and to ensure that others could reproduce the reporting.

Secondly, correlation matrix analysis was worked to discover the multicollinearity among continuous variables before their use in further modeling. Pearson's correlation coefficients were calculated; if a coefficient was > 0.80 variables were examined to verify if they were redundant. In this step, visualization was achieved by using corrrplot package for interpretation of more complex types of correlations.

Third, multilevel linear regression was used with the R package lme4, considering the hierarchical structure of the data, students within schools within regions. This permits for the fact that students could be correlated in some way within the school or region that is unobserved; the independence assumptions of ordinary least squares regression may be violated. Random intercepts were individual for Region and School Type, which means that the random level of the AI literacy intercept score varies across the contextual units, and fixed effects for individual-level predictors were estimated. Intraclass correlation coefficients (ICC) and likelihood ratio tests were used to calculate model fit.

Fourth, the non-linear importance of each predictor and possible interaction effects were assessed using Random Forest machine learning (using the randomForest package). Random Forest algorithms create several decision trees with bootstrap samples of the data and combine their predictions to stop overfitting and promote generalizability. Variable importance was evaluated by two metrics: percent increase in mean squared error (%IncMSE) when the value of a variable was permuted, and increase in node purity, a determine of how much each variable reduced the variance of the outcome. The number of trees was fixed at 500, and variable sampling was turned on to decorrelate the individual trees as well as to enhance the performance of the ensemble.

3.5. Validity, Reliability, and Ethical Considerations

Several techniques have been used for the validity and reliability of the conclusions. Some tools and instruments used in this study were previously validated, and variables were ranged with the previous theories (Bourdieu & Richardson, 1986; Warschauer & Matuchniak, 2010), thereby improving the construct validity of the study. Multilevel modeling was employed to reduce the impact of contextual muddles, and Random Forest analysis was employed to identify and examine non-linear relationships that could inflate or deflate regression estimates of these relationships, enhancing internal validity. Restricted random sampling, also known as stratified sampling, was employed to include representation of key subpopulations to contribute to the external validity of the work and to generalizability of the findings to the larger context of education in Jordan.

Ethical issues were taken into consideration by acquiring the approval of the relevant institutional review boards in Jordan and following the international acceptable guidelines in conducting research. Informed consent of all subjects is obtained (or guardian in case of minors) and all data are de-identified to shield the privacy of the subjects. The team of research contacted by the Ministry of Education to confirm that the actions of data collection were compatible with the national procure and the fallout of the study would be published to the value of the students and teachers in Jordan.

4. Results

4.1. Descriptive Statistics and Bivariate Correlations

The empirical analysis shows that there are noticeable disparities in AI literacy across the Jordanian educational system in terms of geographic, institutional and pedagogical factors. The overall mean score for AI Literacy Score was 62.1 (SD = 15.7) and for Digital Access Score was 58.4 (SD = 18.2), advising that respondents have a relatively low level of technological integration with a outstanding variation across the sample (Table 1). The Socioeconomic Status (SES) Index averaged 2.1 (standard deviation of 0.8) and there was a large perceptual distribution of schools.

Table 1. Descriptive Statistics of Key Variables

Variable	Mean	Std. Deviation	Min	Max
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Digital Access Score	58.4	18.2	10.0	98.5
AI Literacy Score	62.1	15.7	15.0	99.0
Socioeconomic Status (Index)	2.1	0.8	1.0	3.0

Note. N = 1,000. AI Literacy and Digital Access scores are continuous variables scaled from 0 to 100. Socioeconomic Status (SES) is an ordinal index ranging from 1 (Low) to 3 (High), derived from a composite of parental education and household income.

A comparative cross tabulation of mean AI literacy scores is bestowed in Table 4 to give some insight into the spatial and institutional dimensions of any inequalities. Results show a catholic disparity between Amman and the rural areas and the refugee camps: the overall mean for Amman is 71.8, while for the rural areas is 56.3 and for refugee camps is 48.5. Furthermore, there is a noticeable difference between private and public schools where the mean score in private schools in Amman is 78.2 while the mean score in public schools in the migrant camps is 45.8. In this way, the structure imbalance points to the final statement of Warschauer and Matuchniak (2010) that there should be believed of digital equity in access terms, but also in terms of its cumulative effects from multiple socioeconomic and geographic factors. To get a visual picture of the supply of these distributions, Figure 1 shows the AI literacy scores for participants by region, gender and teacher training. One important fact is revealed in the panel 'Teacher Training: Trained': the interquartile ranges for both female and male students and the medians are parallel across all the regions, particularly between Amman and rural areas. By contrast, the gender gap widens in the "Not trained" panel and the general gap increases, especially in the migrant camps. The findings of these pictures are significant and reveal that a pedagogical intervention can help to reduce the gender gap in digitalization historically found in Jordan (Abu-Shanab & Al-Jamal, 2015; Sweidan & Areiqat, 2021).

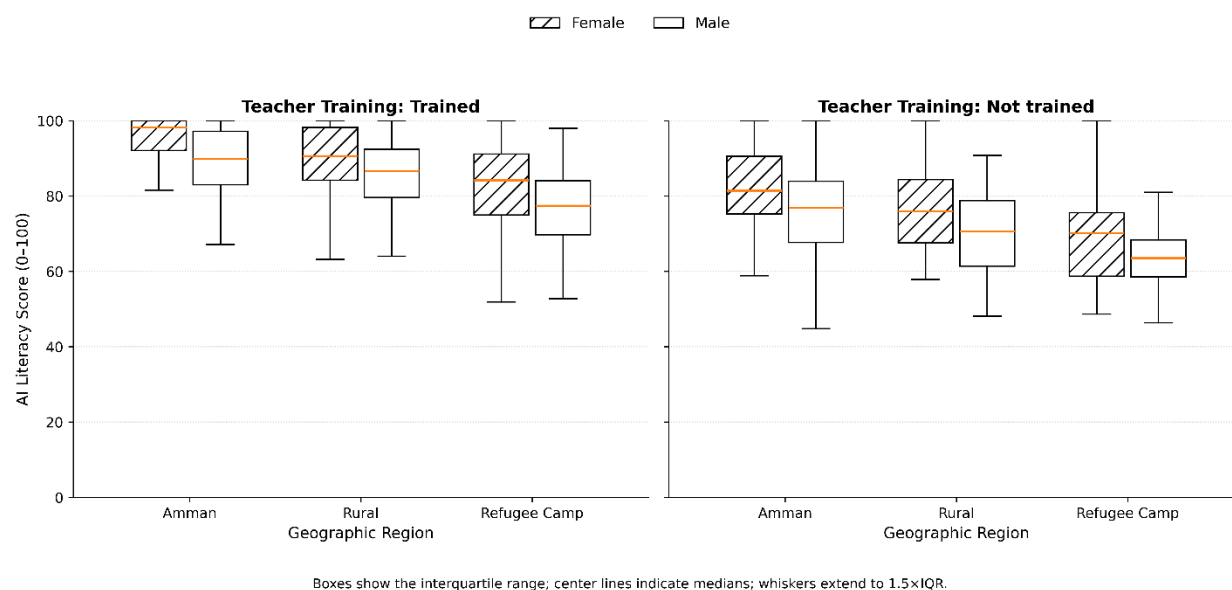


Figure 1. AI Literacy Scores by Region, Gender, and Teacher Training in Jordan

Note. Generated using the ggplot2 package in R. Outliers beyond the $1.5 \times \text{IQR}$ whiskers are omitted from the plot for visual clarity. The hatched pattern denotes female students, while the solid outline denotes male students.

This is presented as a connection heat map between the key variables in this bivariate relationship in Figure 2. The analysis reveals a strong and positive correlation between Digital Access and AI Literacy ($r=0.67$), underscoring the pivotal role of infrastructure in advancing AI literacy. A moderate positive relationship is found between Teacher Training and AI Literacy ($r=0.49$). It is interesting to note that there is very weak correlation between SES and AI

literacy ($r=-0.02$). This counterintuitive finding directs that incomes classroom-based interventions, in the presence of access and teacher training, to mitigate the effects of disadvantaged conditions occurring at the household level (Ma, Vachon, & Cheng, 2019).

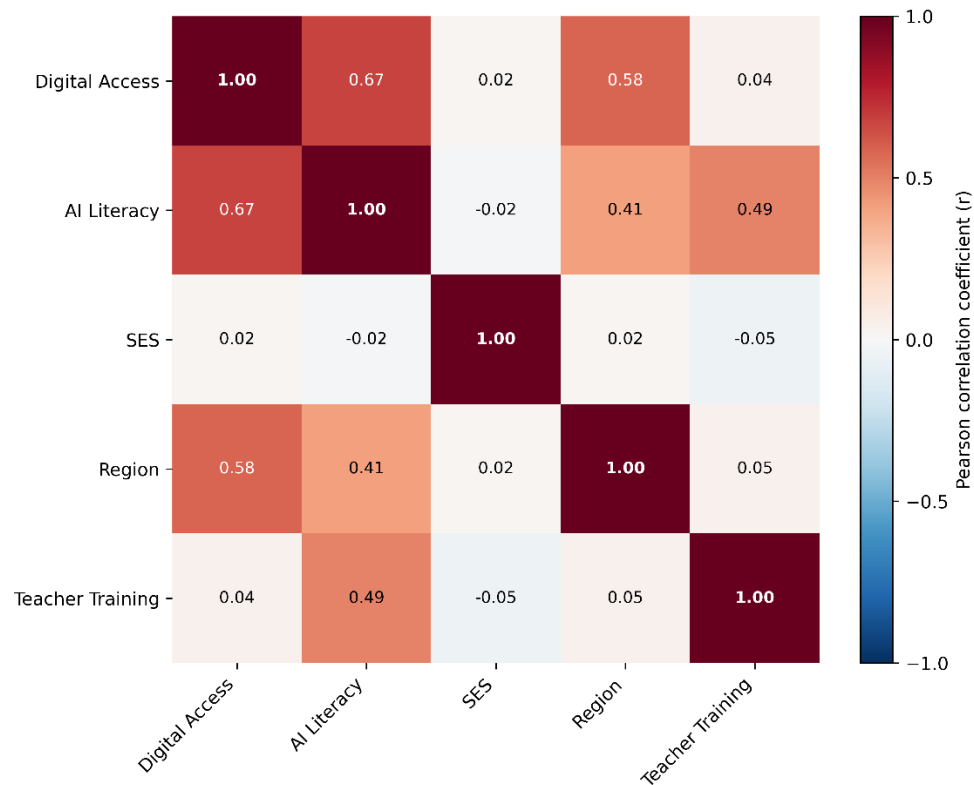


Figure 2. Correlation Matrix of AI Literacy and Digital Equity Variables

Note. Pearson correlation coefficients were computed for continuous variables, and the ordinal/binary variables (Region and Teacher Training) were numerically coded for the matrix computation. Correlations almost zero are marked with white.

4.2. Multilevel Linear Regression Analysis

Because of the hierarchical structure of the data (students are nested within school, school is nested within region), a multilevel linear regression model was estimated. The model fit was good, and its explanatory power was as presented in Table 2.

Table 2. Multilevel Linear Regression Model Summary (Predictors of AI Literacy)

Predictor	Estimate (β)	Std. Error	t-value	p-value
(Intercept)	38.50	2.10	18.33	< .001
Digital Access Score	0.58	0.04	14.50	< .001
Teacher Training (Yes)	8.40	1.85	4.54	< .01
Gender (Female)	3.20	1.50	2.13	< .05
SES (Middle vs Low)	4.10	1.60	2.56	< .05
SES (High vs Low)	7.80	2.00	3.90	< .001
Random Effect: Region	Variance = 12.4			
Random Effect: School Type	Variance = 8.1			

Note. Reference categories for categorical predictors are: Gender = Male, Teacher Training = No, and SES = Low. Significance levels: $p < .05$, $*p < .01$, $**p < .001$. Random effect variances indicate the between-group variability in AI Literacy Scores attributable to the Region and School Type levels, estimated using the lme4 package in R.

The Digital Access Score was the strongest fixed effect predictor of AI literacy ($\beta=0.58$, $SE=0.04$, $p<.001$). AI literacy scores were 0.58 points higher for each additional unit of digital access, while limiting for other variables. Teacher Training was also a very large positive predictor ($\beta=8.40$, $SE=1.85$, $p<.01$), which meant that students working with AI trained teachers tended to score an average of 8.4 higher on the AI literacy scale. The other significant, but smaller, positive effect occurred for gender (female students, $\beta=3.20$, $p<.05$), which more supports the visual evidence from the results on Figure 1 that when gender barriers are addressed, female students perform as well or better. SES had a positive (stepwise) effect, with high-SES students scoring 7.8 points higher than low-SES students ($p<.001$).

Importantly, the arbitrary effects parameters show the structure of the digital divide. The region accounted for 12.4 difference and School Type accounted for 8.1 difference. Based on the intraclass correlation coefficient (ICC), about 15% of the overall variation in AI literacy can be defended by regional and institutional clustering. This is in line with the study by López-Meneses et al. (2025) calling for consequence of spatial and institutional nesting to prevent ecological fallacies and to effectively target policy interventions.

4.3. Machine Learning and Predictive Feature Importance

Although multilevel regression is good for linear relationships, many educational phenomena may be more complexly related. A machine learning algorithm Random Forest was used to model these dynamics. The fallouts of feature importance metrics of the predictive capability complete in Table 3 and illustrated in Figure 3 support and expand upon the regression results.

Table 3. Random Forest Variable Importance Metrics

Variable	% Increase in MSE	Increase in Node Purity
Digital Access Score	24.5	145.2
Teacher Training	18.3	112.8
Socioeconomic Status (SES)	12.1	85.4
Region	9.4	62.1
Gender	4.2	28.5
School Type	3.8	25.0

Note. The % Increase in Mean Squared Error (MSE) suggests the decrease in the precision of the model's prediction that comes from the random permutations of the values of a variable; larger is better predictive importance. Increase in Node Purity: Total reduction in node impurity (variance) from splits on that variable over all the trees.

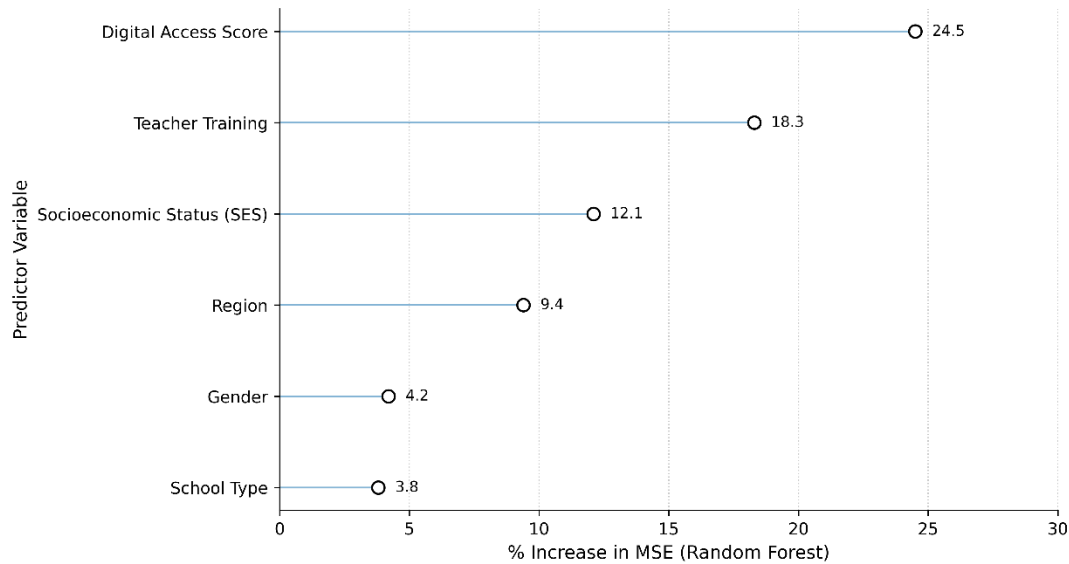


Figure 2. Random Forest Variable Importance for AI Literacy

Note. Importance Metrics are based on a Random Forest model with 500 decision trees. The % Increase in MSE is the % increase in out-of-bag prediction error because of permuting each predictor variable

Digital Access Score was found by the Random Forest model to be the most important predictor with the highest Mean Squared Error (MSE) increase on permutation (24.5%), and the highest node purity increase on permutation (145.2). Teacher Training was second with the start of MSE of 18.3%. Interestingly, SES was the third (12.1% rise in MSE), but the predictive value was greatly less than Digital Access and Teacher Training. Other factors included Region (9.4%) and School Type (3.8%), with lower direct importance indicating that the variance in these factors is captured by the digital infrastructure and pedagogical support variance. Gender (4.2%) was the least important predictor. This machine learning evidence also suggests that reserves in infrastructure and pedagogy implement higher marginal gains for AI literacy than demographic aiming alone and supports resource allocation strategies by the Ministry of Education with a more solid empirical underpinning (Chui et al., 2023; Ali et al., 2025).

4.4. Thematic Synthesis of AI Integration Challenges

To interpret the quantitative outcomes in the wider realm of education, a thematic synthesis was done with reference to the principles of thematic analysis (Braun & Clarke, 2006). Table 4 maps the prime challenges of AI-integrated school in Jordan directly to the statistical differences found in Tables 1-4.

Table 4. Thematic Mapping of AI Integration Challenges in Jordanian Schools

Theme	Description	Supporting Literature
Infrastructural Deficit	Lack of reliable internet and hardware, especially in rural/camp areas.	World Bank (2024); Cotella & Aburamadan (2025)
Pedagogical Unpreparedness	Teachers lack training in AI literacy and prompt engineering.	Ayanwale et al. (2024); Mollick & Mollick (2023)
Socioeconomic Disparity	High cost of private AI tools widens the gap between rich and poor.	Bourdieu & Richardson (1986); Maatuk et al. (2026)
Cultural & Linguistic Barriers	Lack of Arabic-language, contextually relevant AI learning materials.	Hamouda et al. (2025); Hadad et al. (2023)

Note. Themes were deductively synthesized (Braun & Clarke 2006) from the quantitative differences identified in tables 1-4 and then compared with the literature on digital equity and the use of AI in the MENA region.

Table 4. Comparative Analysis of Mean AI Literacy by School Type and Region

Region	Public School (Mean)	Private School (Mean)	Overall Mean
Amman	65.4	78.2	71.8
Rural	52.1	68.5	56.3
Refugee Camp	45.8	61.2	48.5

Note. Numbers are the average AI Literacy Scores (0-100) by each geographic and institutional tier. The "Overall Mean" is the average of the public school and private school means in each region, without giving special weight to either group.

The low baseline scores in Table 5 can be directly attributed to the harsh infrastructural deficits in rural and refugee camp areas (Cotella & Aburamadan, 2025; World Bank, 2024). As shown in Figure 2 and Table 2, the salience of the Teacher Training factor underscores the multifaceted nature of pedagogical under-readiness problem in the education sector (Ayanwale et al., 2024; Mollick & Mollick, 2023). Additionally, the permanent impact of SES, even with the efforts of school-based interventions, suggests entrenched socioeconomic inequities and the prohibitively high cost of private AI tools (Bourdieu & Richardson, 1986; Maatuk et al., 2026). Finally, the cultural and linguistic diversity of students, such as migrants and rural communities, highlights the need for cultural and linguistically relevant AI materials (Hamouda et al., 2025; Hadad et al., 2023). This synthesis also appears that a multi-dimensional approach to digital equity is essential to complete the boxes of the Vision 2033 for Jordan's economic modernization.

5. Discussion and Conclusion

5.1. Synthesizing the Digital Divide and AI Literacy in the Jordanian Context

The empirical findings of this research validate confidence that the social and economic pre-conditions to offer AI education are as important as infrastructure, but not adequate to uphold equity. The wide gap in achievement at geographic and institutional levels illustrates the exhibit of structural inequalities in Jordan. The relevance of these results is tied to the Jordan Economic Modernisation Vision 2033, and the Strategic Plan for Digital Transformation in the Jordanian Ministry of Education (2023-2027) and the critical need to move beyond the facility of hardware (Jordan Economic Modernisation Vision, 2023; Ministry of Education, Jordan, 2023). The World Bank's 2024 findings on technology equity gaps and those of the Department of Statistics, Jordan, 2024, and the Ministry's own AI Integration and Annual Statistical Reports (Ministry of Education, Jordan, 2024a, 2024b), all highlight that digital equity should be evaluated through the tripartite lens of access, use, and outcomes (Warschauer & Matuchniak, 2010). The data shows that there is a clear "Matthew effect" (Stanovich, 2009) with respect to AI literacy: the initial gains in digital capital (Bourdieu and Richardson, 1986; protracted by Musoba and Baez, 2009) continue to grow, resulting in multiplicative impacts on learning. This situation revolts to the known digital gender gap (Abu-Shanab & Al-Jamal, 2015) and its effects on the quality of education in private universities (Sweidan & Areiqat, 2021). Moreover, students' cultural background plays a major role in self-assessment and performance of their digital literacy (Hadad, Watted, & Blau, 2023). The post-pandemic period has only aggravated the e-learning disparity between different socioeconomic statuses (Maatuk et al., 2026), with students facing cognitive dissonance when dealing with poorly designed online education platforms (Ranjan & Mukherjee, 2026). Finally, these differences reflect a larger regional and global phenomenon in which the level of national income, political freedoms, R&D and education investments shape the nature of the second digital divide (Ma, Vachon, & Cheng, 2019).

5.2. The Pedagogical Imperative: Teacher Training and AI Integration

This study is important because it shows that affected teacher training can have a significant impact on reducing the negative impact of socio-economic status and gender on AI literacy. This discovery is in full accordance with the international guidance provided by UNESCO (2023) and Holmes and Miao (2023) that prioritize educator capacity building as the basis of ethical and effective AI integration. The education transformation toward AI-supported pedagogy should be explored as a matter of sociological study of technologies in learning spaces (Bouakaz & Khalid, 2025). As the capabilities of AI grow, so too, the AI literacy that powers them, and it must be carefully planned and designed (Long & Magerko, 2020). Despite this, recent studies indicate that Pre-service Teachers (PSTs) lack AI literacy (Ayanwale et al., 2024) and that there are still misconceptions about machine learning among novice AI teachers (Mühling & Große-Bölting, 2023).

This increase in the need for pedagogical redesign is due to the emergence of Generative AI. As powerful as large language models are for initiating personalized learning experiences, there are deep issues of academic integrity and authorship (Kasneci et al., 2023). To tap into this potential, educators need to grasp effective AI teaching strategies, such as advanced prompt engineering (Mollick & Mollick, 2023), and enter the age of "co-intelligence," in which humans and machines work together harmoniously (Mollick, 2024). Amid the emerging discourses and initial claims made about ChatGPT (Jensen et al., 2025; Watson, 2025), the emphasis needs to be on making critical digital literacies instead of merely adopting new technologies.

5.3. Vulnerable Populations and Contextualized AI Adoption

For vulnerable communities, the need to fairly integrate AI is enormous. However, refugees in camps like Al Baqa' in Jordan face multiple challenges, and digital technologies can also serve as important lifelines for community engagement and blended learning (Cotella & Aburamadan, 2025; Reinprecht et al., 2021; UNHCR, 2024). To attain sustainable, equitable curriculum design in these post-pandemic contexts, amenable, inclusive approaches are necessary (Ramaila, Dhurumraj, & Iraqui, 2025).

Such local challenges are indicative of global trends. The efficacy of virtual schools in rural areas is mostly dependent on longitudinal support and contextualized infrastructure (Hamlin, Adigun, & Adams, 2023) and is emphasized in learning on computing in African contexts, where there is a need for localized learning materials to prevent the deepening of the technological divide (Hamouda et al., 2025). More largely, education status is linked to digital infrastructure and policy change in the MENA region (Fakih et al., 2025). In-depth comparative analyses of Asian higher education literature (Giray et al., 2024) indicate that cautious monitoring of the use of Generative AI in student learning, especially in the field of mathematics education (Lin & Jiang, 2025), is necessary to avoid its negative consequences, such as the addiction to Generative AI (Wu, Huang, & Lin, 2026). Moreover, the unique nature of different educational fields, such as language education (Liang et al., 2023) and music education (Mazlan et al., 2026), explains that adopting AI is not a universal challenge.

5.4. Theoretical Implications and Critical Perspectives

Effective interventions require trustworthy AI frameworks focused on transparency, accountability, and human oversight to guarantee that AI integration is for the public good (Ma, Li, Hu, Liu, & Cheong, 2025). Generative AI has the amazing potential to spur economic growth and has been called the next productivity frontier (Chui et al.,

2023), which makes it important to critically consider its role in education. There are systemic reviews which warn that educators and institutions may not be prepared for this loose change (Zawacki-Richter et al., 2019; Popenici & Kerr, 2017), and that while AI promises are exciting (Holmes, Bialik, & Fadel, 2019), there is a need for a realistic understanding of machine learning and human intelligence (Luckin, 2018).

But as Selwyn (2025) cautions, we must be guarded of ‘technological solutionism’; the notion that technology can provide the solution to every social problem. Rather, one needs to think radical and new about the future of the digital and "digital degrowth" – designing a future in which AI worsens no environmental and social inequalities. From a limited resource perspective like Jordan, this means that focus should be presented not only to interventions that are cutting-edge rather than impactful, but resource-intensive, but also to environmental and impactful pedagogical interventions.

5.5. Methodological Reflections and Future Directions

This study is methodologically a showcase of what Computational methods can offer to Education research. Educational data mining requires efficient algorithms to identify any decorations of inequity between large numbers of data, like large-scale astronomical surveys that are designed to search for weak, high-latitude signals amongst a mass of data (Downes et al., 2004). This study integrates the epistemological robustness of supported theory (Charmaz, 2014) and thematic analysis (Braun & Clarke, 2006) with state-of-the-art predictive modeling and submissions as a powerful framework for analysing educational disparities. Focus for future studies should be to grow these bibliometric and predictive models (Ali et al., 2025) through the addition of longitudinal research designs that can discover the long-term impacts of AI intervention on student labour market readiness and lifelong learning journeys.

5.6. Conclusion

Finally, there is a need for a redirection from infrastructure to pedagogy and equity policies to address an “AI literacy divide” in Jordan. Findings lend a strong empirical case for the magnitude of targeted professional learning and place-based tech access as fragile elements of AI literacy that can address socioeconomic and geographical marginalization. The Ministry of Education must work towards Professional Development, culturally responsive curriculum design, and dependable AI governance to accomplish the goal of human capital development in the Jordan Economic Modernization Vision 2033. When it comes to general educational equity, Jordan can be a leader in illustrating this vision and thinking about how to river the digital transformation process.

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