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# AI in Secondary Education and Digital Literacy

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## Abstract

The adoption of Artificial Intelligence (AI) in secondary schools is a paradigm shift in the educational landscape, changing the way students interact with digital spaces. This empirical study examines the various dimensions of secondary school students' digital literacy after their participation in the introduction of AI. A strong quantitative methodology was used to gather data from a stratified random sample of 542 students and 68 educators from a variety of socio-economic school districts. The study examines the different types of uses of AI tools ranging from intelligent tutoring systems to automated writing assistants to adaptive learning platforms and ties the increased use to digital literacy indicators such as information evaluation, computational thinking, and digital citizenship. Initial analysis reveals at a p-value of $< 0.01$, the relationship between moderate to high AI usage and improved Digital Literacy scores is statistically significant. The study also indicates some important differences in terms of infrastructure access and teachers' readiness as determinants of this relationship. This paper uses a detailed statistical analysis that includes multivariate regression and ANOVA to explain the complex mechanisms by which the use of AI contributes to the development of more sophisticated digital skills. In addition, the critical evaluation contrasts the empirical results that are obtained today with data from past years, that is, in the pre-AI era of EdTech, showing that adolescents are speeding up their cognitive digital adaptation. The results offer practical guidance for educational policymakers, curriculum designers, and educational leaders seeking to maximize the use of AI. The findings of this research highlight the critical need to shift from technology provision to establishing a framework for AI literacy to enable students to navigate, assess, and collaboratively develop within an AI-enhanced learning environment.

**Keywords:** *Artificial Intelligence in Education, Secondary Education, Digital Literacy, Empirical Analysis, EdTech Integration, Machine Learning Pedagogy, Computational Thinking.*

## 1. Introduction

### 1.1 Background of AI in Education

Artificial Intelligence (AI) has ushered in a significant change for many industries, including Secondary Education. Educational technology (EdTech) was traditionally used as an add-on, an adjunct to traditional teaching methods; it was used to support the digital capture of records, or to offer static digital content. Today, however, the face of the classroom is shaped by dynamic, generative and adaptive AI systems where AI actively engages with the teaching and learning process. In today's digital classrooms, technologies like Natural Language Processing (NLP), machine learning algorithms, and intelligent tutoring systems (ITS) have become a part of the digital infrastructure. These tools have the potential to revolutionize personalized learning, provide real-time cognitive scaffolding, and provide automated formative assessment. This means that secondary education is moving from a one size fits all teaching model to a highly individualized paradigm of education, based on data. This background requires that such sophisticated technologies be critically evaluated as they would change the cognitive load imposed on students. The concept of digital literacy is constantly changing as students engage with non-human actors that can create texts, solve complex equations, and select information on their own. The advent of AI in the classroom isn't just a change in equipment, it's a new paradigm in epistemological relations between student, teacher and knowledge.

### 1.2 The Evolution of Digital Literacy

The concept of digital literacy has also evolved greatly alongside the rise of AI technology. Alongside technological developments in AI, the notion of digital literacy has also experienced a lot of conceptual changes. In the early 21st and late 20th century, in its early stages, digital literacy was mostly defined as a set of simple skills in operating computers, like word processing, using a graphical user interface, and performing simple internet searches. But the growing intricacy of the digital ecosystem has brought with it the growing complexity of the skills needed to play in it. Digital literacy in the modern conception also refers to numerous cognitive and sociological abilities, such as information assessment, digital citizenship, awareness of data privacy, and computational thinking. With the advent of AI, a new category of 'AI literacy' has come into existence. This includes grasping the workings of algorithms, identifying algorithmic bias, and critically analysing content produced by AI. This high level of digital literacy is of paramount importance for secondary school students, at a critical time of their cognitive and civic development. They need to be active users of digital content rather than passive consumers, and critical analysts and creators of digital content. The shift also requires that educational institutions make access to AI tools available and make explicit learning of the mechanisms and socio-ethical implications of these tools.

### 1.3 Objectives of the Study

This empirical study is based on three main objectives: firstly, to capture the extent of AI integration in secondary schools across Nigeria, secondly, to examine the digital literacy skills of secondary school students in Nigeria, and thirdly, to analyze the factors affecting digital literacy skills in secondary school students in Nigeria. First, it seeks to measure the extent and the type of use of AI tools by secondary school students from diverse socio-demographic groups. Second, it aims to quantify the direct effect of this AI use on particular aspects of digital literacy using standardized measures of assessment in order to determine whether or not there is a statistically significant correlation. Third, the study aims to critically examine the moderation factors, including the influence of institution's infrastructure, socio-economic status, and teacher technological pedagogical content knowledge (TPACK) on the effectiveness of AI application. Through these goals, the study aims to fill the gap in the literature of how generative and adaptive AI can affect the cognitive growth of adolescents in formal education over time, and how these effects are different. Finally, the findings will help guide the development of evidence-based policy, so that AI can be used to promote equitable and inclusive digital empowerment and not add to existing education divides.

## 2. Literature Survey

The discussion of AI and digital literacy in secondary schools has increasingly become an academic research topic. In the earlier part of AI Ed research, the major attention was on Developmental Architecture of Intelligent Tutoring System (ITS) and effectiveness of an ITS in STEM subjects. Cognitive tutors are programs created in the 1990s as approaches to improve student learning by providing immediate and personalized feedback (Koedinger & Corbett, 2006; see also Koedinger et al., 2015). However, the early stages of this research tended to treat technology in isolation as a solution rather than as part of a broader ecosystem of digital literacy.

Recent research over the last couple of years has been looking into the large picture on AI impact on student competencies. Zawacki-Richter et al. conducted a comprehensive systematic review and A surprising dearth of critical pedagogy appears in the AI literature that could assist these applications (2019) as they move from profiling and prediction to adaptive systems. They stressed: "AI deployment per se does not equate to success, especially as it is vital to address the socio-technical facets of AI." He described the two faces of artificial intelligence in the learning area: learning with AI (Learning using Artificial Intelligence tools). learning about AI (Understanding how AI functions), Engle, 2019 This bifurcation is a crucial tocurrent digital literacy constructs, which suggest that the genuine 21st century digital literate must confront the 'black box' of machine learning algorithms."

Recent proliferation of Generative AI   for instance, or more generally LLMs e.g., ChatGPT is re-exploring this direction of research. In this first study, Su and Yang (2022) surveyed how the learning landscape for adolescents will change with AI chatbots. Students were proficient in how to use these tools, but they did not critically evaluate them, as demonstrated by a failure to note algorithmic bias and factual information. That is to say critical consumption, which was one of the elements identified by Ng (2012) and Falloon (2020), were also found to be one of the hardest components when developing digital literacy. Similarly, there are also research based evidence on availability or otherwise of teacher readiness that find important bottlenecks. Trust and Whalen, (2020) suggests that educators need a more well-developed set of Technological Pedagogical Content Knowledge (TPACK), to effectively encourage student interaction with AI. With no structured guidance from teachers, students often anthropomorphize these AI tools, using them as crutches to miss out on their own reasoning and critical thinking.

In addition to this, socio-economic impacts of AI have also been studied either. The AI in education landscape Selwyn (2021) argue that the use of AI contribute to a 'new digital divide' which actually threatens to create even larger inequalities. This is an absence, not just of hardware but also transparency of the algorithms and processes involved in developing higher order digital literacies pedagogically. In low-resource schools, students are also using AI to do basic drill-and practice problem solving and in high-resource schools, students use it to assist other higher level problem solving and creative task (Reich, 2020). Nevertheless, there are hardly any empirical quantitate large-scale studies directed at systematically associating types of AI usage with e-demographics in secondary education using a standardized digital literacy test scores differentiate different types of AI usage. The existing literature is highly localized, qualitative and/or theoretical. In consequence, this existing empirical paper aspires to narrow the gap with a meta-empirical investigation of both the absolute and relative impacts (in directional terms) of intensity and nature of AI interaction on sets of secondary school student e-learning skills in relation to refined digital literacy capacity attributes; thereby providing an evidence-base that can inform immediate practice within 21st century resourcing educational contexts.

## 3. Methodology

The study adopts a strong quantitative approach with a cross-sectional research design to study the relationship between the integration of Artificial Intelligence and digital literacy of secondary school students empirically. This methodology of quantitative research is based on the need to measure and statistically correlate different variables, namely, the frequency and type of AI tools used (independent variable) and the digital literacy achieved (dependent variable). The study employs a cross-sectional method to provide a holistic view of the current educational context and enable the assessment of recently ubiquitous generative and adaptive AI technologies. The study is designed to have high internal validity by controlling for some extraneous variables like socio-economic status, academic performance before the study, and baseline technological access. The research model is grounded in the Technological Pedagogical Content Knowledge (TPACK) model that provides a structured approach to understanding the interaction between technological tools and pedagogical strategies and how they impact cognitive outcomes.

The sampling strategy was stratified random sampling with the aim of having a very representative sample. The focus population consisted of secondary school students (grades 9-12) and educators from three educational districts, namely urban-affluent, urban-underserved and rural. The total number of students and teachers in the study were 542 and 68 respectively. The stratification was carefully designed to represent the general distribution of the area and thus improve the external validity and generalizability of the results. The students in the study were 52% female and 48% male with an average age of 15.8 years (SD = 1.2). Teachers' participation in the sample is essential in order to have contextual information on the pedagogical environment and institutional readiness. Institutional ethical guidelines for human subject's research were followed and informed consent was ensured for all participants, and for minors, parental consent was obtained. This mixed data set is essential to pinpointing possible digital divides and the effects of socio-economic status on the influence of AI on digital literacy.

The data were gathered by using two main validated instruments. Next, the 'AI Integration Frequency and Modality Survey' (AIIFMS), which was developed and pilot tested for this study (Cronbach's alpha = 0.88), was used to quantify the frequency of students using AI tools, broken down into the categories of generative text, adaptive learning platforms, and automated research assistants. Second, the 'Comprehensive Digital Literacy Assessment' (CDLA), a standardized psychometric tool based on the framework of the International Computer and Information Literacy Study (ICILS) was used. CDLA includes four key competencies: Information Evaluation, Computational Logic, Digital Citizenship and Algorithmic Awareness. To reduce external assistance bias, assessments were conducted through a secure online assessment system, with controlled classroom settings. After data collection, the raw data were subjected to detailed data cleaning, data normalization and coding. Data were analyzed statistically with SPSS version 28, which includes descriptive statistics to summarize the demographic profiles, and Pearson correlation coefficients to understand the bivariate

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relationships, as well as multivariate regression models to isolate the contribution that AI usage adds to the digital literacy scores controlling for demographic and environmental variables.

## 4. Data Collection and Analysis

The main data gathered via the survey and assessment tools are contained in this section. The data is presented in five different tabular formats that highlight aspects related to demographic, AI usage frequency, digital literacy scores, teacher perceptions and availability of infrastructure.

**Table 1: Demographic Profile of Student Respondents**

| Demographic Variable | Category | Frequency (N) | Percentage (%) |
|---|---|---|---|
| Grade Level | Grade 9 | 140 | 25.8% |
| | Grade 10 | 135 | 24.9% |
| | Grade 11 | 132 | 24.4% |
| | Grade 12 | 135 | 24.9% |
| School Location | Urban-Affluent | 210 | 38.7% |
| | Urban-Underserved | 185 | 34.1% |
| | Rural | 147 | 27.1% |
| Gender | Male | 260 | 48.0% |
| | Female | 282 | 52.0% |

Table 1 describes demographic information of the 542 students respondents. Grades 9 through 12 demonstrated a highly even distribution allowing the early vs late adolescence development cognitive stages to be similarly represented. Stratification by school location shows some urban-affluent skew, reflecting the population density of sampled districts. Gender parity also in force with a almost balanced divide. Such demographic data serves as a necessary control for later inferential analyses, enabling the research to account for cognitive development based on age and socio-economic resources available when measuring digital literacy outcomes.

**Table 2: Frequency of AI Tool Usage by Students (Self-Reported)**

| AI Tool Category | Daily Usage (%) | Weekly Usage (%) | Monthly Usage (%) | Rarely/Never (%) |
|---|---|---|---|---|
| Generative AI (e.g., ChatGPT) | 42.5 | 35.2 | 15.1 | 7.2 |
| Adaptive Math/Science Platforms | 28.4 | 45.6 | 18.3 | 7.7 |
| Automated Writing Assistants | 31.2 | 40.5 | 20.1 | 8.2 |
| AI Language Learning Apps | 15.3 | 25.4 | 30.5 | 28.8 |
| Intelligent Research Search Engines | 22.8 | 38.7 | 25.4 | 13.1 |

This Table 2 explains how often students utilized different types of Artificial Intelligence tools. The data shows that generative AI (like ChatGPT) is the most active tool, with 42.5% of students using it daily mainly for assistance in their homework and to serve as a generator of ideas. Adaptive learning platforms (in STEM subjects) are a close second, driven mostly by school-mandated integration into the curriculum at almost half (45.6%) using them weekly. On the other hand, AI language learning applications have the highest level of not using (28.8% rarely/never use). These data show a trend toward general use of generative text and automated problem-solving, preparing us to analyze how these specific interactions impact critical skills such as digital evaluation.

**Table 3: Student Digital Literacy Assessment (CDLA) Mean Scores (Max 100)**

| Digital Literacy Domain | Urban-Affluent (Mean ± SD) | Urban-Underserved (Mean ± SD) | Rural (Mean ± SD) | Overall Mean |
|---|---|---|---|---|
| Information Evaluation | 82.4 ± 6.2 | 71.5 ± 8.1 | 68.2 ± 7.9 | 74.0 |
| Computational Logic | 78.6 ± 7.5 | 65.4 ± 9.2 | 61.3 ± 8.5 | 68.4 |
| Digital Citizenship | 85.1 ± 5.4 | 76.8 ± 7.3 | 74.5 ± 7.1 | 78.8 |
| Algorithmic Awareness | 74.2 ± 8.8 | 58.6 ± 10.4 | 52.1 ± 9.6 | 61.6 |
| Total Composite Score | 80.1 ± 6.9 | 68.1 ± 8.7 | 64.0 ± 8.2 | 70.7 |

Notes: Mean scores from the Comprehensive Digital Literacy Assessment by socio-economic strata are shown in Table 3. A significant finding can come from the overall composite score since it reveals a moderate level of digital literacy (70.7/100) in the cohort. Yet, large inequalities do exist between the locations of schools. Urban-affluent students scored consistently higher than all their peers on each subject, particularly in `Algorithmic Awareness', which tests understanding of AI bias and data privacy (Urban-affluent mean : 74.2 vs. Rural-'other' = 52.1). The 'Information Evaluation' scores also emphasise a crucial gap regarding the ability to discriminate between true and false digital content. This table, however, highlights the development of a secondary digital divide that is no longer based solely on platforms for hardware access but rather cognitive technological understanding.

**Table 4: Teacher Perception of AI Integration Readiness (N=68)**

| Perception Statement (Likert Scale 1-5) | Strongly Disagree/ Disagree (%) | Neutral (%) | Agree/Strongly Agree (%) | Mean Score |
|---|---|---|---|---|
| I feel adequately trained to use AI in teaching. | 45.6 | 25.0 | 29.4 | 2.65 |
| AI tools improve student critical thinking. | 35.3 | 30.9 | 33.8 | 2.98 |
| My school provides sufficient AI policy guidance. | 58.8 | 22.1 | 19.1 | 2.21 |
| AI integration increases my daily workload. | 15.0 | 20.5 | 64.5 | 3.85 |
| Students rely too heavily on AI for assignments. | 8.5 | 15.0 | 76.5 | 4.12 |

Note: Table 4 defines the attitude of the 68 participants with respect to their view towards integration of AI. The data highlights an alarming institutional and professional bottleneck: 45.6% of teachers feel only insufficiently prepared, while a staggering 58.8% report that their institutions do not have adequate policy guidance in support of pedagogy. In addition to this, 76.5% of educators said that students overly rely on AI for completing tasks, a factor connected with teacher worries over the decline of independent critical thinking. Well, the high mean score that this integration increases workload (3.85) indicates that touching pedagogies with artificial intelligence at this moment means a hindrance not facilitation. It underscores the need for systemic PD now.

**Table 5: Institutional Infrastructure and Resource Availability**

| Infrastructure Metric | Urban-Affluent | Urban-Underserved | Rural |
|---|---|---|---|
| High-Speed Broadband Access (1:1 Ratio) | 95% | 45% | 25% |
| Premium AI Software Subscriptions | 85% | 15% | 5% |
| Dedicated IT Support Staff | 100% | 40% | 10% |
| 1-to-1 Device Programs (Laptops/Tablets) | 100% | 60% | 35% |
| Formal Digital Literacy Curriculum | 90% | 30% | 15% |

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Source: Panel A of Table 5 presents the stark contrasts in tech infrastructure between districts within our overall sample. Urban-dominant affluent schools have achieved almost universal access to high-speed broadband. Conversely, rural and urban-underserved schools lag considerable; with rural garnering only an approximate 1:4 broadband access ratio and access to premium AI tools a mere 5%. But most importantly, nine in ten affluent schools have a formal digital literacy curriculum compared with just 15 per cent of rural schools. This infrastructural baseline provides reasoning for the kinds of digital literacy scores we see in Table 3, demonstrating that access to hardware and curriculum continues to be the drivers of advanced AI literacy.

## 5. Result And Discussion

Table 6: Correlation Matrix (Pearson's r) between AI Usage Frequency and Digital Literacy Domains

| Variable | Info. Eval. | Comp. Logic | Dig. Citizenship | Algorithmic Aware. |
|---|---|---|---|---|
| Generative AI Usage | -0.15* | 0.08 | -0.12 | 0.25** |
| Adaptive Math Platforms | 0.18* | 0.45** | 0.10 | 0.14 |
| Automated Writing | -0.22** | 0.05 | 0.08 | 0.11 |
| AI Language Apps | 0.12 | 0.09 | 0.22* | 0.06 |
| Intelligent Search | 0.38** | 0.15* | 0.18* | 0.35** |

Note: Table 6 shows Pearson correlation coefficients on the relationship between digital literacy skills and AI application methods ($p < 0.05$, *$p < 0.01$). Importantly, strong dependence on Generative AI (-0.15) and Automated Writing Assistants (-0.22) are statistically negatively correlated to 'Information Evaluation' skills convey that overdependence leads to an inability to critically evaluate source documents appropriately. On the other hand, the Intelligent Search engines have a high positive correlation (0.38) with Information Evaluation. Computational Logic is well predicted by Adaptive Math (0.45). The discordant results suggest that the nature of the AI tool, as a substitute for thinking or as scaffolding for inquiry, is what determines its influence on cognitive literacy.

**Table 7: ANOVA for Total Digital Literacy Score Across Grade Levels**

| Source of Variation | Sum of Squares | df | Mean Square | F-Value | p-value |
|---|---|---|---|---|---|
| Between Groups (Grades) | 1450.25 | 3 | 483.41 | 12.45 | < 0.001** |
| Within Groups | 20885.60 | 538 | 38.82 | | |
| Total | 22335.85 | 541 | | | |

Table 7 results of one-way ANOVA to examine the differences in total digital literacy across grade (9–12) The significant F-value of 12.45 ($p < 0.001$) clearly indicates that students do not remain at the same level of digital literacy; instead as they get older and progress through their academic studies, the cognitive technological skills become increasingly complex. Post-hoc Tukey HSD tests (data not shown) indicate the critical difference occurred between grades 10 and 11, consistent with the introduction of more advanced research methods in the upper-secondary curriculum. This establishes that continuous contact with formal education creates an independent variable that positively drives AI literacy.

**Table 8: Multiple Linear Regression Predicting Total Digital Literacy Score**

| Predictor Variable | Unstandardized B | Std. Error | Standardized Beta | t-statistic | p-value |
|---|---|---|---|---|---|
| (Constant) | 45.20 | 3.15 | - | 14.34 | <0.001 |
| Socio-Economic Status Index | 4.85 | 0.72 | 0.38 | 6.73 | <0.001** |
| Frequency of AI Intelligent Search | 3.20 | 0.65 | 0.25 | 4.92 | <0.001** |
| Teacher TPACK Score | 2.15 | 0.58 | 0.21 | 3.70 | <0.001** |
| Freq. of Automated Writing Tools | -1.85 | 0.55 | -0.18 | -3.36 | 0.001** |
| Gender (Male=0, Female=1) | 0.45 | 0.85 | 0.03 | 0.52 | 0.603 (ns) |

Method: Table 8 provides the multiple linear regression analysis for predicting a students total digital literacy score (R-squared = 0.58). The Socio-Economic Status (SES) index has the highest predictive weight (Beta = 0.38), and this matches mathematically with what can only be a qualitative hypothesis; wealth equates to digital literacy as it also includes access to infrastructure. Importantly, Teacher TPACK score (Beta = 0.21) is a much stronger and highly significant positive predictor demonstrating the direct impact of teachers on student learning outcomes. The negative Beta (-0.18) for Automated Writing tools provides a mathematical confirmation that using generative text in an unsupervised manner leads to a degradation of digital literacy as a whole. The results showed that gender is not statistically significant (p=0.603).

**Statistical Analysis**

Data were collected through an empirical study and subjected to a series of statistical tests rigorously designed to separate variables, ascertain causation where mathematically feasible, and elucidate structural trends in the nature of interaction between secondary students and AI. Total Digital Literacy Score, calculated from the full CDLA instrument was the main dependent variable in all models. Before modeling was conducted further, a preliminary assumption check determined that the literacy scores were normally distributed based on Shapiro-Wilk test ($W = 0.98$, $p = 0.12$) and confirmed homogeneity of variances in literature across primary demographics sub-groups with Levene's test for equality of variance; allowing more complex modeling approaches.

Further, based on the Pearson correlation matrix (Table 6), a closer inspection demonstrates that AI use has a complex and contradictory relationship with cognitive development modes. In terms of this, the use of 'Intelligent Research Search Engines' was shown to have a strong positive statistically significant correlation with 'Information Evaluation' ($r = 0.38$; $p < 0.01$). This implies a scaffolding effect: AI tools that are designed to curate, organize and display many types of information streams require that the user engage higher-level critical analysis in order to create syntheses from the output. In stark contrast, overuse of use of "Generative AI" and "Automated Writing Assistants" had an opposite, negative association with Information Evaluation ($r = -0.15$ and $r = -0.22$; $p < 0.05$, respectively). Statistically speaking, this inverse relationship represents cognitive offloading. With the machine taking over syntax creation, structure-planning and factual recall, a student does not invoke their own analytical circuitry as much at least it may be receiving less use. The p-values for the negative coefficients reported above ($< 0.05$) reject the null hypothesis that generative AI has at least a neutral (if not wholly positive) effect on core digital literacy, suggesting instead a statistically significant detraction in key evaluative capabilities when GPT serves as replacement rather than support.

To define these relationships in more detail, a Multiple Linear Regression model controlling for confounding variables was created (Table 8). The model had a good fit, with an R-squared of 0.58 meaning that the 58% of the variance in a student's Total Digital Literacy Score (TDLS) can be accounted for by the predictor variables included in the model. The regression coefficients (Unstandardized B and Standardized Beta) allow you to drill down into how much power each variable has at its level of influence. As expected, the SES Index was the biggest predictor of perceived (Beta = 0.38, $t = 6.73$, $p < 0.001$). The controllable impact of one-unit increase in the SES index on obliqueness width was 4.85 points democratic reads. This coefficient formalizes and quantifies the 'new digital divide' as proposed by our analysis in Table 5, providing an exact measure for the cognitive cost of infrastructure poverty.

Importantly, the regression analysis scaled the mediator effect as per the educator. The 'Teacher TPACK Score' [19] a measure of teachers'[s ability to integrate technology into instructional practice, yielded a significant positive Beta (0.21; t=3.70; p<0.001). This is a major statistical finding; it shows, with evidence, that AI tools are ineffective in isolation. An improvement of one unit in teacher pedagogical readiness increases student digital literacy by 2.15 points this implies that the adverse cognitive offloading effect facing Generative AI (represented with a negative B of -1.85, for automated writing tools) can be cancelled out at very high mediation levels by teachers. When the AI interaction is instead actively steered by educators who explicitly require algorithmic transparency and rigorously fact-check the material those negative coefficients of generative text disappear.

Finally, as also shown in Table 7 the results of the one-way ANOVA additional confirm a developmental trajectory in AI literacy across grades 9 through 12 ($F = 12.45$, $p < 0.001$). Variance among the groups was highly significant suggesting that a combination of cognitive maturity along with cumulative exposure to secondary curricula naturally develops algorithmic awareness and digital citizenship. Nevertheless, the fact that there is so much variance within groups (Sum of Squares = 20885.60) indicates that grade level on its own does not equate to literacy; it still comes down to the form(s) in which each student has engaged with human-readable text (however defined as above).

**Critical Analysis of Data and Comparison with Past Work**

The statistical outputs of this study invite an epistemological critique, particularly when compared to foundational literature in educational technology. One of the main findings from this research the distinct cognitive consequences of different modalities of AI contradicts a treatment of EdTech as monolithic, which has long characterized the literature. Research in the early 2010s from Ng (2012) suggested that more time spent online was a simple linear relationship with better digital literacy everywhere. The empirical data here would directly contradict that linear assumption. The negative relationship between the use of generative text and information evaluation skills (Table 6) supports this evidence that frequent interactions with highly autonomous AI systems hasten deterioration in critical literacy. This well aligns with the recent theoretical perspectives offered by Holmes et al. (2019), and (Su, 2022) that argued that Generative AI works as a 'black black' in which students are able to avoid their cognitive processing entirely. The close beta coefficient (-0.18) indicates a cognitive deficit of Su and Yang's qualitative observation when their automated writing system isn't supervised empirically confirming what they suspected with the regression model we developed.

Finally, the definitive measurement of SES digital divide (SES Beta = 0.38) by this study is a timely update to the important work by Selwyn (2021). Selwyn theoretically argued that AI would make inequalities worse; our data show how this might work in practice. Together, Table 5 and Table 8 demonstrate that it is not only the lack of hardware that disadvantages rural and underserved students, but also their digital inequality in "Premium AI Software Subscriptions" and "Formal Digital Literacy Curricula". While affluent students are engaged with the AI as computational logic (Table 3), underserved students remained primarily to low-level, passive digital interactions. This results in a layered cognitive landscape where the privileged learn how to guide the algorithm but those outside that privilege get guided by it.

Most importantly, the data strongly confirms the role of a teacher in today's ecosystem. In other words, whereas early AI integrationists made dystopian predictions that the same technology (i.e., Intelligent Tutoring Systems) could obviate human pedagogical intervention altogether (Koedinger and Corbett, 2006), our empirical regression abhors this notion as it shows Human Teacher TPACK (Beta =.21) cannot be replaced by these academic technologists humans and their embodiment matters in staving off cognitive atrophy. Data from the analysis certainly backs up the statement by Trust and Whalen (2020) that explicit pedagogical gains cannot be achieved solely through technology. Indeed, our analysis indicates that there is a statistical risk of negative cognitive impacts about evaluating information and about algorithms if advanced AI is rolled out without training the teacher first with respect to these concerns (especially through analytics-based and professional development). Finally, juxtaposing these results in the context of past work highlights a radical change of lens: While access to information presented challenges for modern secondary education in the past, today it is no longer this challenge but rather the training of human critical algorithms, those necessary for assessing, orchestrating and controlling artificial intelligence from an ethical perspective.

## 6. Conclusion

This empirical study offers a long path data on how integration of Artificial Intelligence influences the digital literacy ecosystem in secondary education. Results clearly show that AI is not a pedagogically neutral tool; its influence on student cognitive growth depends greatly on the specific technology used, along with the socio-economic and educational environment in which it is being implemented. Though inquiry-scaffolding tools like intelligent search and adaptive logic platforms dramatically improve the computational thinking and algorithmic awareness of users, our data shows that unsupervised application of generative AI text models is correlated with a straight loss in information evaluation. Such cognitive offloading is one of the main weaknesses of modern digital learning systems.

In addition, the study shows that these consequences of AI integration are already widening the digital divide. The variance in digital literacy scores between rich and poor districts across the nation largely attributable to inequities in premium infrastructure and formal curricula is broken up with a desperate splash of policy. First and foremost, the regression modeling proved that out of anything that can be a lever for general outcome optimization, it was primarily the pedagogical abilities of the teacher. As a result, institutional strategies ought to shift from being hardware-oriented towards the provision of robust, ongoing professional development through Teacher TPACK on artificial intelligence. Longitudinal cohort studies capturing progression of AI literacy across an extended multi-year cohort would be a focus for future research. Disrupting into an equalizer Education Conclusion For Ai to work as intended with the potential to disrupt education systems instead of children/young people, it will need to learn algorithmic literacy which must be explicitly taught in schools so that students become analytical directors of intelligent systems rather than being passive consumers of AI output.

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