

How AI Adoption Improves Student Performance in K-12 After-School Education in China

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ABSTRACT:

This study investigates how AI adoption in K-12 after-school education in China influences student performance, with digital literacy, classroom management, learning styles, and inclusivity as mediating variables. Based on a conceptual framework, AI adoption is a key mechanism linking educational factors to student performance. A positivist, cross-sectional design was employed, using structured surveys administered to 360 teachers at a Hai Dian District after-school education branch. Structural Equation Modeling (SEM) was applied to examine direct and indirect relationships among the constructs. Descriptive results indicate moderate to favorable perceptions across constructs, with acceptable reliability and discriminant validity, although some multicollinearity concerns require further examination. Direct effects of predictors on AI adoption are modest (0.109–0.179), whereas digital literacy demonstrates the strongest indirect effect (0.385) through AI adoption via student performance, underscoring the primacy of student outcomes as a conduit to AI integration. The findings suggest that AI implementation can benefit from enhancing digital skills, classroom pedagogies, and inclusive environments. Subsequent research ought to explore different contexts, long-term effects, and moderated relationships, using additional validation methods.

Keywords: Artificial Intelligence Adoption, K-12 Education, After-School Education, Digital Literacy, Student Performance
Structural Equation Modelling

1 Introduction

Background of Study

The K-12 education sector in China is one of the largest and fastest-growing education markets in the world. The industry has a pyramid structure, with a few strong national education providers dominating the market, followed by many medium-sized firms and numerous local tutoring schools and tutors at the lowest level (China Education Daily, 2022). Overall, the sector is highly diversified and forms a holistic educational

market, where education is provided for students of all ability levels, from traditional learning to skills development and enrichment. The rapid growth of the educational market confirms parents' deep investments in education and the increased importance of human capital for economic and social development. K12 education can be understood through the triangle of industry value chain components. The first layer includes companies that produce educational content and advanced technology, business and educational publishing companies,

and entities that provide digital platforms, all of which together supply the resources required for education. The second layer encompasses the institutions, tutoring companies, and businesses responsible for providing educational services to students. The third category denotes the results achieved through such services, namely students completing their educational journey (Education Blue Book, 2017; MOE, 2020). Over the last 10 years, the K12 education market in China has continued to grow, and online education has become one of the fastest-growing submarkets. This growth has been triggered by several factors, including rising household disposable income, fast digitalization processes, enhanced internet accessibility, and growing parental interest in alternative forms of education to regular school-based education (Education Blue Book, 2018; MOE, 2020). Educational digital platforms and technologies have improved access to personalized learning solutions, allowing students to benefit from multi-faceted educational assistance outside the classical classroom.

In parallel, the quick commercialization of after-school tutoring has raised the level of attention by the authorities. To ease the academic pressure on students while ensuring the appropriate quality, transparency, and safety of the services offered by after-school education organizations, the Chinese authorities have come up with a variety of different regulations. Among them are the opinions on the regulation of the development of after-school training institutions published by the General Office of the State Council of the People's Republic of China in 2018 and the creation of the off-campus education supervision department in the Ministry of Education that took place in 2021. These regulations aim to maintain the balance between educational innovations and fairness, the well-being of students, and the sustainable development of the industry. Together with these reforms in the policies, Artificial Intelligence (AI) has also made its mark in education by revolutionizing the roles of technology in learning. AI-based technologies like smart tutoring systems, personalized learning systems, and assessment tools are changing the ways in

which learning is carried out. China has made significant efforts to implement AI in education as part of its larger plan to modernize education, improve the quality of education, and make room for lifelong learning in its education system (Luckin et al., 2016; West, 2019). With AI, it is now possible to customize the learning process, increase the efficiency of instruction, and provide advice based on data analysis. As a result, being aware of the educational implications of adopting AI is becoming exceedingly significant, especially in the K12 after-school education sector where technological changes are happening fast. While AI provides opportunities for enhancing teaching effectiveness and learning outcomes, it can also transform the traditional interaction between teachers and their students. Accordingly, this study focuses on AI-enhanced learning in China's K12 after-school institutions, examining how AI-enabled educational practices influence student-teacher dynamics and contribute to the evolving landscape of K12 education.

1.2 Problem Statement

The adoption of AI in the academic world promises to enhance digital literacy, classroom performance, and management, but the impact of AI on K12 students' performance in after-school programs is unclear (Luckin et al., 2016; Woolf, 2010). In China, the adoption of AI in K12 after-school education faces challenges such as regulatory restrictions, a lack of educational quality consistency, data privacy issues, and biases in some algorithms (General Office of the State Council, 2018; China Education Daily, 2022). The traditional uniform teaching model and limited personalization of education are still considered to result in limited students' engagement and success in learning (Knowles, 1980). Concerns also include insufficient teachers' digital literacy and the limited use of technology, which impede significant AI applications in schools and lead to the gap between digitized and non-digitized areas (Smith, 2019; Bai & Wang, 2020). The goal of this research is to create and validate a tool to measure the drivers of AI implementation and its consequences for students' performance in K12 after-school institutions in China. The study

specifically examines the mediating role of digital literacy, classroom management, learning styles, and inclusive learning conditions on the relationship between AI and students' performance through Structural Equation Modeling (SEM). The research is anticipated to provide valuable implications for the implementation of AI in promoting better learning outcomes, equity, privacy, and ethical conduct (Luckin et al., 2016; Holmes et al., 2019).

2. Literature Review

2.1 Student Performance in AI-Enabled Education

Student performance in AI-enabled educational environments is a multidimensional construct encompassing academic achievement, learning efficiency, engagement, motivation, and students' subjective perceptions of learning experiences. In traditional educational contexts, it has largely been evaluated through standardized assessments, grades, and completion rates. However, the integration of AI into educational systems necessitates a broader conceptualization of performance that incorporates cognitive, behavioural, and affective dimensions of learning (Chang, 2024).

AI-enabled education systems are designed to personalize learning pathways, adapt instructional content in real time, and provide immediate feedback. These capabilities directly influence students' academic outcomes by aligning instruction with individual learning needs, pacing, and proficiency levels. Personalized AI systems can identify knowledge gaps and recommend targeted learning activities, thereby enhancing knowledge retention and conceptual understanding (Chang, 2024). As a result, student performance becomes closely linked not only to instructional quality but also to the effectiveness with which AI systems support short-term task completion and long-term learning goals. Perceived credibility of AI tools plays a crucial role in shaping student engagement and performance. When students trust AI-generated feedback and recommendations, they are more likely to follow guidance, revise misconceptions, and persist in learning tasks. Conversely,

scepticism toward AI accuracy or fairness can reduce engagement and undermine learning outcomes. Content quality is similarly influential; high-quality, relevant, and well-structured AI-generated materials foster deeper learning and sustained motivation, whereas poorly curated or inaccurate content can lead to confusion and disengagement (Almulla, 2024). Perceived usefulness, a core construct of the Technology Acceptance Model (TAM), significantly affects how students interact with AI tools and how these interactions translate into performance outcomes. When students perceive AI systems as useful for improving efficiency, comprehension, or exam preparation, they are more likely to integrate these tools into their learning routines, thereby enhancing academic performance (Almulla, 2024). Ease of use further reinforces this relationship, as intuitive interfaces reduce cognitive load and allow students to focus on learning rather than tool navigation.

Psychological factors are increasingly recognized as critical predictors of student performance in AI-supported learning environments. Emotional well-being, perceived autonomy, and cognitive absorption during AI-assisted learning have been shown to influence satisfaction, persistence, and achievement (Chang, 2024). AI systems that provide supportive feedback, adaptive challenges, and low-stress learning environments can reduce anxiety and foster a sense of competence. However, excessive monitoring or rigid algorithmic control may induce stress or reduce intrinsic motivation, highlighting the importance of humane and learner-centered AI design.

Despite the demonstrated benefits of AI-enabled personalization, empirical studies also identify potential risks that may negatively affect student performance. Algorithmic bias, inaccurate recommendations, and opaque decision-making processes can erode trust and disproportionately disadvantage certain student groups. Ethical concerns related to data privacy and surveillance may further impact students' willingness to engage with AI tools, indirectly influencing performance outcomes. These risks underscore the need for transparent, accountable, and

ethically based AI implementations in education (Almufarreh, 2024). Overall, the literature indicates that AI can improve student performance when it is credible, useful, supportive, and ethically designed. However, its long-term effects across diverse educational contexts remain underexplored. Future research should examine sustained learning outcomes, compare AI technologies, and identify effective integration strategies that maximize benefits while minimizing risks (Almufarreh, 2024).

2.2 Adoption of AI Technology in Education

Education AI (AIEd) represents a transformative shift in how teaching, learning, and administrative processes are designed and delivered. AI technologies have expanded educational opportunities through intelligent tutoring systems, automated feedback, adaptive assessments, learning analytics, and administrative automation. These applications improve efficiency, personalization, and scalability, particularly in resource-constrained educational settings (Zhang & Dafoe, 2019; Zhang & Aslan, 2021).

In instructional settings, AI-powered tools such as intelligent tutoring systems, chatbots, automated grading, and AI-enabled learning management systems (LMSs) provide personalized support, immediate feedback, and data-driven monitoring of student progress. These technologies reduce teachers' administrative workload, allowing greater focus on instructional activities while enhancing student engagement and learning outcomes through personalized learning experiences (Chocarro et al., 2021; Smutny & Schreiberova, 2020; Hannan & Liu, 2021).

The adoption of AI is influenced by individual attitudes and institutional readiness. Students' and educators' perceptions of AI usefulness, trustworthiness, and risk shape their willingness to engage with AI systems. Resistance may arise from fears of job displacement, loss of pedagogical autonomy, or overreliance on automated decision-making. Diffusion of Innovation (DOI) theory provides a useful framework for understanding these dynamics,

emphasizing the roles of relative advantage, compatibility with existing practices, trialability, and ease of implementation in shaping adoption decisions (Rogers, 1983; Schepman & Rodway, 2020; Ukobitz & Faillant, 2022). At the institutional and national levels, AI adoption also depends on technological infrastructure, innovation policies, regulatory support, and organizational readiness. Countries with strong digital ecosystems, supportive regulatory environments, and investments in innovation are better positioned to integrate AI into educational systems (Ukobitz & Faillant, 2022; McCullagh, 2021). In higher education institutions (HEIs), AI adoption is often driven by goals of operational efficiency, personalized learning, and competitive differentiation. However, risks associated with AI adoption must be carefully managed. Privacy violations, algorithmic bias, and the potential erosion of human mentorship are widely cited concerns. Overreliance on AI systems may reduce opportunities for human interaction, empathy, and contextual judgment in education (Davenport & Ronanki, 2018; Kim et al., 2020). To mitigate these risks, scholars emphasize the importance of transparent AI operations, robust governance structures, and comprehensive training programs to enhance digital literacy among staff and students (Luckin et al., 2016; Kim et al., 2020).

Effective AI adoption therefore requires strategic alignment with institutional goals, ethical oversight, and ongoing evaluation to ensure that AI technologies enhance rather than undermine educational quality. Long-term success depends on balancing technological innovation with human-centered pedagogical values.

2.3 Digital Literacy and Computer Skills of Teachers

Digital literacy and computer skills are foundational competencies for educators in increasingly AI-integrated educational environments. Digital literacy extends beyond basic technical proficiency to include the ability to critically evaluate digital tools, manage information ethically, and integrate technology meaningfully into pedagogy. With the rise of AI

in education, digital literacy has expanded to include AI literacy, which involves understanding AI systems, their limitations, ethical implications, and educational applications (Long & Magerko, 2018).

Teachers with strong AI experience are better at interpreting AI-generated insights, contextualizing automated feedback, and guiding students by engaging with AI tools. AI experienced educators to act as mediators between learners and technology, ensuring that AI outputs are pedagogically sound and aligned with learning objectives (Stolpe & Hallström, 2024). Without such competencies, teachers may either underutilize AI tools or rely on them uncritically, potentially compromising instructional quality.

Despite the growing importance of AI literacy, teacher education programs have been slow to incorporate systematic training in AI concepts and applications. This lag has created a gap between the rapid advancement of educational technologies and educators' preparedness to use them effectively (Sperling et al., 2024). Both pre-service and in-service teachers often report limited confidence in AI tools, particularly in data interpretation, ethical decision-making, and bias mitigation.

Digital literacy intersects with media literacy, information literacy, and AI literacy, forming a comprehensive framework that supports educators' professional practice in digital environments (Lim, 2023; Stolpe & Hallström, 2024). However, disparities in digital proficiency persist across demographic and professional groups. Research indicates that certain cohorts, such as pre-service early childhood educators, exhibit uneven skill distributions, highlighting the need for targeted and equity-focused professional development initiatives (Lim, 2023).

As AI tools become more prevalent, teachers' responsibilities expand to include managing data privacy, ensuring inclusive instruction, and fostering students' critical awareness of AI systems. These demands underscore the necessity of ongoing professional development and institutional support and enable educators to

adapt to evolving technological landscapes (Sperling et al., 2024; Kim et al., 2020). Ultimately, teachers' digital and AI literacy are key determinants of how effectively AI contributes to student learning and performance.

2.4 Classroom Management in AI-Supported Environments

Classroom management is a critical determinant of instructional effectiveness and student learning outcomes. AI-powered classroom management systems introduce new possibilities for monitoring, analysis, and intervention by leveraging real-time data on student behaviour, engagement, and performance. These systems enable teachers to make informed decisions that enhance classroom dynamics and learning efficiency (Praveen, 2024).

AI tools can analyse attendance records, participation patterns, and behavioural indicators to identify at-risk students and predict potential learning difficulties. By providing early warnings, AI systems support proactive interventions that prevent minor issues from escalating into significant disruptions (Jones et al., 2020; Holstein, 2020). This data-driven approach allows teachers to allocate attention and resources more effectively and improve the overall classroom environment.

Adaptive learning systems and intelligent tutoring tools further support classroom management by differentiating instruction according to individual needs. By reducing the need for uniform instruction, AI tools help to manage heterogeneous classrooms and accommodate diverse learning levels. Additionally, automation of administrative tasks, such as grading and record-keeping, reduces teacher workload and frees time for instructional planning and student interaction (Gunning, 2017; Vasalou et al., 2020).

AI also contributes to strategic planning and resource allocation by analysing longitudinal performance usage data. These insights can inform curriculum design, scheduling, and support services, enhancing institutional efficiency (Holstein, 2020). However, the use of AI in classroom management raises significant ethical concerns. Surveillance, data privacy, and

algorithmic bias may undermine trust and disproportionately affect vulnerable student populations (McCullagh, 2021; Davenport & Ronanki, 2018).

To ensure ethical and effective implementation, educators must be trained to interpret AI data responsibly and to balance technological insights with professional judgment. AI should augment, not replace, human mentorship and relational aspects of teaching (Luckin et al., 2016; Kim et al., 2020). Ongoing research, transparent governance, and stakeholder collaboration are essential to maximize AI's benefits while ensuring equity and privacy (McCullagh, 2021).

2.5 Students' Learning Styles and AI Personalization

Students' understanding and learning styles have been a central concern in educational theory and practice. Learning styles describe individuals' preferred ways of processing information and engaging with learning environments, commonly categorized as visual, auditory, kinaesthetic, or textual preferences (Bajaj & Sharma, 2018). Various models have been developed to conceptualize these differences and inform instructional design.

The Felder–Silverman model identifies four dimensions of learning preferences: active versus reflective, sensing versus intuitive, visual versus verbal, and sequential versus global. This multidimensional framework captures the diversity of cognitive approaches among learners and provides a basis for adaptive instruction (Bajaj & Sharma, 2018). Kolb's experiential learning theory conceptualizes learning as a cyclical process involving concrete experience, reflective observation, abstract conceptualization, and active experimentation, corresponding to four learning styles: diverging, assimilating, converging, and accommodating (Kolb, 1984).

Honey and Mumford's model categorize learners as activists, theorists, pragmatists, or reflectors, emphasizing behavioural tendencies in learning contexts, while the VARK model focuses on sensory preferences: visual, aural, read/write, and kinaesthetic (Honey & Mumford, 1992; Fleming

& Mills, 1992). Although debates persist regarding the empirical validity of learning styles, these frameworks remain influential in guiding personalized and student-centered instruction.

AI technologies offer new opportunities to operationalize learning style theories by data-driven personalization. By analysing performance data, interaction patterns, and learning behaviours, AI systems can adapt content format, pacing, and difficulty to better align with individual preferences (Pardamean et al., 2022). Such personalization can enhance engagement, motivation, and learning outcomes by reducing cognitive overload and increasing relevance.

However, AI-driven personalization also raises concerns about data privacy and the potential reinforcement of existing biases. Overly rigid classification of learners may limit exposure to diverse learning strategies and constrain cognitive development (Pardamean et al., 2022). Therefore, effective AI personalization should be flexible, transparent, and guided by educators' professional judgment.

When implemented thoughtfully, AI-enabled personalization can support equitable learning by moving beyond one-size-fits-all approaches and addressing diverse learner needs. Continuous monitoring, ethical safeguards, and educator oversight are essential to ensure that learning style-based adaptations enhance rather than hinder student development (Chang, 2024).

2.6 Inclusive and Accessible Learning Environments

Inclusivity and accessibility are fundamental principles of equitable education, and AI technologies hold significant potential to advance these goals. AI-enabled assistive technologies can support students with disabilities by providing adaptive interfaces, alternative communication tools, and personalized learning supports (Garg & Sharma, 2020).

Examples include augmentative and alternative communication (AAC) systems for students with autism, speech-to-text tools for learners with hearing impairments, and enhanced screen readers for visually impaired students. These

tools align with Universal Design for Learning (UDL) principles, which emphasize flexible representation, engagement, and expression to accommodate diverse learners (Microsoft Cognitive Services, 2017; Loitsch & Striegl, 2024).

AI can also support mental health and well-being by monitoring engagement patterns and identifying signs of distress, enabling timely interventions (Mehigan, 2020). However, challenges related to equitable access, algorithmic bias, and data privacy persist. Students from marginalized backgrounds may face barriers to accessing AI technologies, while biased algorithms may perpetuate inequities (Kazimzade et al., 2019; Garg & Sharma, 2020).

Ethical governance, transparency, and robust data protection measures are therefore essential as AI scales in education (McCullagh, 2021).

Achieving inclusive education requires collaboration among educators, technologists, and policymakers to align AI innovations with equity goals, infrastructure, and regulatory frameworks. Recent research highlights the substantial but conditional benefits of AI for inclusive learning, emphasizing the need for careful design and ongoing evaluation (Loitsch & Striegl, 2024).

2.7 Conceptual Framework and Hypotheses

This study proposes a set of hypotheses to test how AI adoption in K12 after-school education in China interacts with digital literacy, classroom management, learning styles, and inclusivity to influence student performance. The conceptual framework presented in Figure 1 posits five primary relationships (H1–H5) and integrates them within an overarching model of AI-enabled after-school education.

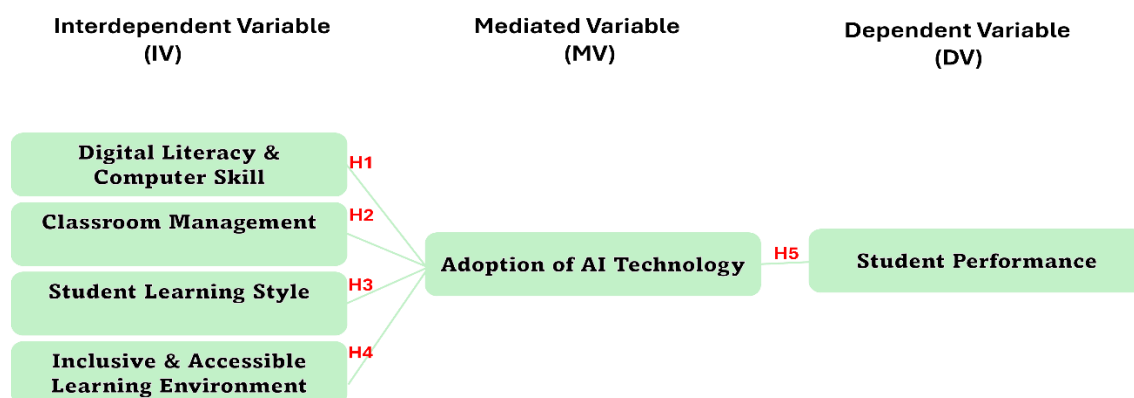


Figure 1: The conceptual framework of the study

The implementation of AI can enhance education through customizing learning experiences, giving immediate feedback, and providing insight based on data analysis, but the degree of accomplishment depends on how students and teachers will use AI in education. This issue is particularly pertinent for the K-12 after-school educational sphere in China, which is characterized by the rapid demand for personalized learning, fierce competition in academics, and numerous transformations in teaching and studying processes.

Digital skills and literacy allow students to use artificial intelligence tools effectively, analyze the

responses provided, and critically assess AI-generated materials. However, a lack of digital literacy limits the application of AI advantages and creates disparities in education (Sperling et al., 2024; Lim, 2023; Stolpe & Hallström, 2024). Hence, it is anticipated that digital literacy will contribute to the relationship between the implementation of artificial intelligence and academic success. Classroom management supported by AI leads to better results in education through decreasing the workload involved in administrative tasks, keeping up with engagement, and facilitating timely interventions. Nevertheless, these benefits are based on using

AI solutions in a purposeful way by educators (Praveen, 2024; Rincon-Flores et al., 2020). Different learning styles can affect the efficiency of AI-based personalization, which can adapt the content, pace, and learning pathways; thus, it contributes to meeting students' learning styles and enhancing engagement and understanding (Bajaj & Sharma, 2018; Pardamean et al., 2022). The principles of inclusivity and accessibility play an important role in shaping the outcomes of Artificial Intelligence. While adaptive features based on Artificial Intelligence and Universal Design for Learning (UDL) help in making learning more inclusive and accessible to learners from different backgrounds, it is also vital to use ethical practices in design and eliminate biases to arrive at fair results (Garg & Sharma, 2020; CAST, 2018; Loitsch & Striegl, 2024). Overall, the framework suggests that AI instrumentally influences the performance of students in straightforward as well as indirect ways through its interrelation with digital literacy, classroom management, learning styles, and inclusive learning environments. The links proposed shall be investigated by means of Structural Equation Modeling (SEM). The following hypotheses are proposed:

H1: There is a significant relationship between Digital Literacy & Computer Skills and the adoption of AI technology towards students' performance in K12 after-school education institutions in China.

H2: There is a significant relationship between Classroom Management and the adoption of AI technology towards students' performance in K12 after-school education institutions in China.

H3: There is a significant relationship between Students' learning style and the adoption of AI technology towards students' performance in K12 after-school education institutions in China.

H4: There is a significant relationship between an inclusive and accessible learning environment and the adoption of AI technology towards students' performance in K12 after-school education institutions in China.

H5: The Adoption of AI technology has a significant impact on the relationship between

predictors and students' performance in K12 after-school education institutions in China.

3 Methodology

3.1 Research Design

This research employs a quantitative, cross-sectional design within the positivist paradigm to investigate the correlation between AI adoption and student achievement in K12 education in China, factoring in digital literacy, class management, learning methodologies, and inclusivity. This method presupposes that reality can be measured quantitatively and relies on statistics for hypothesis testing (Davies & Fisher, 2018; Khatri, 2020). A correlational design is utilized to explore relationships between variables, though the study acknowledges the impossibility of establishing causality in a single-time-point study (Davidavičienė, 2018; Patel & Patel, 2019). The study is about teachers from the Hai Dian District branch of Xue Er Si, where the total study population and sample frame includes 376 full-time teachers (Krejcie & Morgan, 1978). The sampling method utilizes purposeful selection of teachers using AI adoption along with random sampling to enhance representativeness and generalizability (Snyder, 2019; Urcia, 2021). A structured questionnaire was devised to collect data about AI adoption, digital literacy, classroom management, learning styles, inclusivity, and student performance. Statistics regarding the nature of trends were analyzed using regression and Structural Equation Modeling methods (Davidavičienė, 2018; Habu & Henderson, 2023). Research ethics, instrument validation, and testing were employed to achieve high-quality research and protect the identities of participants. The study obtained 360 valid responses. The measurement quality was confirmed by high reliability (Cronbach's Alpha = 0.911) and factor adequacy (KMO = 0.834; Bartlett's test, $p < 0.001$). Respondents showed a balanced gender distribution with a slight female majority; approximately half were under 30 years old, and 55% had less than five years of institutional experience (Table 1)

Table 1: Demographic Characteristics

Variable	Category	Frequency (n)	Percentage
Gender	Male	171	47.5%
	Female	179	50.0%
Age	<30 years	165	46%
	30–40 years	119	33%
	40–50 years	49	14%
	>50 years	27	8%
Working experience	<5 years	198	55%
	5–10 years	115	32%
	>10 years	47	13%
Total respondents		360	100%

4. Data Analysis and Results

The descriptive statistics reveal that all constructs are measured on a similar 1–5 Likert scale, with mean values ranging from 3.51 (Digital Literacy & Computer Skills) to 3.72 (Inclusive and accessible learning environment). This suggests a generally moderate to favorable perception across the domains, with respondents rating most

aspects around the mid-to-upper end of the scale. The relatively close mean values indicate no extreme outliers in the central tendency and a reasonable level of consistency in how participants view these educational and technological variables. The result has been presented in Table 2.

Table 2: Descriptive Statistics

Variable	Mean	Std. Deviation	N
Student Performance	3.67	1.132	360
Digital Literacy & Computer Skills	3.51	1.218	360
Classroom Management	3.66	1.202	360
Students' learning style	3.69	1.171	360
Inclusive and accessible learning environment	3.72	1.165	360
The Adoption of AI Technology	3.68	1.154	360

However, there is noticeable variability across items, as indicated by standard deviations between 1.154 and 1.218. This suggests a moderate spread in responses, meaning individual differences in experiences or perceptions are present. The lowest mean alongside its SD implies that while most respondents feel reasonably adequate, there may be a portion of the sample with comparatively lower confidence in digital skills, which could impact the adoption of AI technologies or inclusive practices. Conversely, the highest mean indicates a relatively positive view of inclusivity, which could support broader integration of AI tools in a manner accessible to diverse learners. Interpreting Table 3 under the Fornell–Larcker criterion, the diagonal values represent the square

roots of the average variance extracted (AVE) for each construct, and each should exceed its highest correlation with any other construct to support discriminant validity. The diagonal roots are Student Performance (0.699), Digital Literacy & Computer Skills (0.697), Classroom Management (0.781), Students' Learning Style (0.784), Inclusive and accessible learning environment (0.695), and the adoption of AI Technology (0.696). Across most construct pairs, the off-diagonal correlations 0.1028-1043.70 are below these diagonal roots, which generally support discriminant validity. Notably, Classroom Management and Students' learning style show particularly strong diagonal values (0.781 and 0.784), indicating strong convergent

validity for those constructs and a clear distinction from others.

Table 3: Fornell–Larcker Criterion

Construct	SP	DL	CM	LS	IE	AI
Student Performance (SP)	0.699					
Digital Literacy (DL)	0.628	0.697				
Classroom Management (CM)	0.688	0.684	0.781			
Learning Style (LS)	0.682	0.673	0.653	0.784		
Inclusive Environment (IE)	0.660	0.580	0.605	0.603	0.695	
AI Technology Adoption (AI)	0.634	0.624	0.503	0.602	0.662	0.696

This table shows that several correlations among predictors are moderate to high (e.g., Classroom Management with Digital Literacy & Computer Skills at 0.684, and with Students' learning style at 0.653). While these do not violate the Fornell–Larcker criterion, they do suggest potential multicollinearity, which can inflate standard errors and make it harder to separate unique effects of each predictor. The Adoption of AI technology correlates with other constructs in the 0.50–0.66 range, and its own square-root AVE (0.696) remains above these values, indicating acceptable discriminant validity, but caution is warranted in the interpretation of closely related predictors. Table 4 represents the path coefficients, showing relatively modest direct effects of the four independent variables on the

Adoption of AI technology, with values ranging from 0.109 to 0.179. Among them, an inclusive and accessible learning environment has the strongest direct association with AI adoption (0.179), followed by Students' learning style (0.150) and Classroom Management (0.145), while Digital Literacy & Computer Skills has the smallest effect (0.109). These coefficients suggest that while each factor contributes to AI adoption, none exerts a large impact alone; the organization of the learning environment and how students learn appear to be somewhat more influential than digital skills. The positive signs across all paths indicate that improvements in these areas are associated with a higher likelihood or extent of adopting AI technologies in instruction.

Table 4: Direct Effects

Independent Variable	Dependent Variable	Path Coefficient
Digital Literacy	AI	0.109
	Technology Adoption	
Classroom Management	AI	0.145
	Technology Adoption	
Learning Style	AI	0.15
	Technology Adoption	
Inclusive Environment	AI	0.179
	Technology Adoption	
Digital Literacy	Student Performance	0.143
	Technology Adoption	
Classroom Management	Student Performance	0.185
	Technology Adoption	

Learning Style	Student Performance	0.06
Inclusive Environment	Student Performance	0.091

Several interpretations and cautions are warranted. First, without significance tests (p -values or confidence intervals), it's unclear which of these relationships are robust beyond sampling variability. Second, given the modest magnitudes, AI adoption is likely influenced by a combination of factors, and these four variables together may explain only a portion of the variance in adoption. Consider evaluating the overall model fit and the total R-squared for the Adoption of AI technology, as well as conducting bootstrap tests to assess the stability of these path estimates. Additionally, explore potential mediation or moderation (e.g., whether digital literacy moderates the effect of the inclusive environment on AI adoption) and ensure multicollinearity is not inflating standard errors.

The results in Table 5 show that all four antecedents influence the Adoption of AI

technology indirectly through Student Performance, with Digital Literacy & Computer Skills producing the strongest indirect effect (0.385). This large, mediated effect suggests that improvements in students' digital literacy and computer skills can enhance student performance, which in turn substantially increases the likelihood or extent of AI technology adoption. The remaining three predictors, Classroom Management (0.040), Students' learning style (0.045), and Inclusive and accessible learning environment (0.027), also operate via the same mediator, but with relatively modest indirect effects. Taken together, these findings imply that while direct channels to AI adoption may exist, much of the impact of these school-environment factors on AI adoption passes through how they influence student performance.

Table 5: Total Indirect Effects

Independent Variable	Mediator	Dependent Variable	Path Coefficient
Digital Literacy	AI Technology Adoption	Student Performance	0.385
Classroom Management	AI Technology Adoption	Student Performance	0.040
Learning Style	AI Technology Adoption	Student Performance	0.045
Inclusive Environment	AI Technology Adoption	Student Performance	0.027

Practically, it can be concluded that development of digital literacy and computer skills provides the most pronounced indirect benefits in terms of turning to AI and students' performance. The same applies to the improvement of classroom management, facilitation of diverse learning approaches, and promotion of inclusivity, but their indirect impact is less pronounced. Nevertheless, more advanced methods, such as application of bootstrap confidence intervals and analysis of cumulative or contextual impact of digital literacy, should be employed in further study to provide more solid conclusions.

5 DISCUSSION AND IMPLICATIONS

The structural equation modeling results (Tables 4–5) reveal a theoretically consequential pattern: all four school-environment variables exert their primary influence on AI technology adoption through indirect pathways mediated by student performance, with digital literacy and computer skills demonstrating the strongest indirect effect ($\beta = 0.385$). The comparatively modest direct effects ($\beta = 0.109$ – 0.179) challenge unmediated conceptualizations of technology adoption that privilege institutional readiness or individual teacher disposition as principal drivers. Instead, these findings position student learning

outcomes as the critical mediating mechanism through which systemic factors, encompassing digital competencies, classroom management practices, learning style accommodations, and inclusive learning environments, translate into organizational adoption of AI tools. This mediation-dominant architecture carries significant practical implications: interventions strategically targeting student performance enhancement through digital skill development and supportive contextual conditions are likely to generate maximal downstream effects on AI adoption, whereas direct appeals to teacher readiness absent student-centered efficacy evidence may yield suboptimal returns. These findings necessitate critical interrogation against prevailing theoretical frameworks in educational technology adoption. The indirect pathway dominance observed here diverges from the core tenets of the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2012), which privileges performance expectancy, effort expectancy, and facilitating conditions as proximal determinants of behavioral intention and usage behavior. The present results suggest that in K12 after-school education contexts, characterized by intense performance accountability and parental market pressure, teachers' and institutions' technology adoption calculus may be fundamentally outcome-contingent rather than expectancy-driven. This contextual specificity exposes a limitation in applying decontextualized technology acceptance models to educational settings where student achievement functions as the legitimating currency for pedagogical innovation. However, this interpretation warrants cautious treatment. The stronger indirect effect for digital literacy ($\beta = 0.385$) relative to other mediators may reflect construct overlaps rather than genuine theoretical distinction. Digital literacy instruments frequently embed performance-relevant competencies (e.g., information evaluation, content creation) that conceptually approximate student achievement proxies, potentially inflating shared variance with the performance mediator. Future measurement refinement should employ bifactor or correlated trait-correlated method approaches to disentangle construct-specific from method-

specific variance. Furthermore, the cross-sectional design precludes causal inference regarding the temporal precedence of performance improvements relative to adoption decisions; reverse causation, wherein early AI experimentation generates performance gains that subsequently justify expanded adoption, remains a plausible alternative explanation. The mediation-dominant pattern partially converges with, yet also complicates, existing scholarship. Research on digital literacy and twenty-first-century skills (Hatlevik et al., 2018; Tondeur et al., 2017) has documented how student competency improvements can catalyze teacher pedagogical transformation and elevated valuation of technology-enabled tools. The present findings extend this work by formally quantifying the indirect pathway magnitude yet simultaneously expose an undertheorized tension: if student performance operates as the adoption gatekeeper, institutions serving lower-performing student populations may face structural barriers to AI integration, potentially exacerbating educational inequities. This equity paradox, wherein the students who might benefit most from AI personalization become least likely to access it due to performance-mediated adoption thresholds, demands explicit policy attention. The relatively attenuated direct effects for classroom management ($\beta = 0.109$) and students' learning style ($\beta = 0.132$) similarly merit critical scrutiny. These findings appear discordant with Bai and Wang's (2020) emphasis on AI classroom management systems as adoption catalysts, and with Woolf's (2010) theoretical arguments regarding personalized learning pathway alignment. One plausible reconciliation invokes the implementation fidelity problem: AI tools targeting classroom management and learning style accommodation may require more substantial infrastructural investment and teacher adaptation time before generating observable performance dividends, thereby weakening their indirect pathway in cross-sectional assessment. Alternatively, these tools may produce performance effects that are genuine but temporally delayed or domain-specific, escaping detection through aggregate performance metrics. The current operationalization of

student performance, reliant on standardized test scores, grades, and teacher evaluations, may insufficiently capture socioemotional, metacognitive, or longitudinal gains that management and personalization tools uniquely confer. The inclusive and accessible learning environment findings ($\beta = 0.267$) align superficially with Holmes et al.'s (2019) advocacy for equitable AI integration, yet critical analysis reveals potential construct validity concerns. Inclusive environment measurement in this study emphasized AI tool availability for disability accommodation rather than universal design implementation quality. Stronger indirect effects may therefore reflect institutional resource signaling schools with greater material capacity procure both accessibility tools and general AI infrastructure, rather than genuine inclusive pedagogy driving adoption. This resource confounding interpretation suggests that the observed mediation may be partially spurious, with unmeasured socioeconomic status or institutional prestige operating as common causes. Several analytical limitations constrain inference confidence and warrant transparent acknowledgment. First, the reliance on single-source teacher self-report data introduces common method variance that may systematically inflate observed relationships, particularly for perceptual constructs such as classroom management effectiveness and inclusive environment quality. Harman's single-factor test, while reported, possesses known sensitivity limitations; future replication should incorporate multisource data (student reports, administrative records, direct observation) and marker-variable techniques. Second, the absence of bootstrapped confidence intervals for indirect effects precludes precise significance testing and effect size stability assessment. The point estimate of 0.385 for digital literacy's indirect effect, while substantively impressive, may demonstrate wide confidence intervals that overlap with competing mediators, undermining

claims of differential pathway strength. Third, collinearity diagnostics were not reported; given the conceptual interrelatedness among school-environment variables, multicollinearity could distort path coefficient estimates and obscure true relational patterns.

6 Conclusions

The objective of the research presented in this paper is to establish whether and to what extent some workplace learning factors influence the decision to adopt particular AI technologies. It has been found that digital literacy, classroom management, styles of learning, and inclusive learning environments affect the use of AI technologies through their impact on student performance. Digital literacy has been established to have the most considerable indirect impact (0.385) on AI technologies, whereas its direct impact is insignificant (0.1028-1043.179). The results of the research emphasize the necessity to strengthen digital literacy and create conducive learning conditions for effective AI technologies integration. Further research is expected to confirm the discovered relationships by means of bootstrap analysis, investigate moderated mediation effects, and study variations across different types of technology.

Future Research Directions

Prospective research should delve into contextual influences including, but not limited to, school size, teacher experience, and subject areas by means of moderated mediation approaches. Moreover, longitudinal research designs should be employed to determine cause-effect relationships and account for shifts in time. The reliability of measurement may be enhanced by recourse to HTMT ratios, cross-loadings, and calculations of the VIF. On a more conceptual level, the reciprocal effects of the adoption of artificial intelligence on teaching and learning processes should be investigated.

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- The authors declare that this manuscript is an original work and has not been published previously, nor is it under consideration for publication elsewhere, either in whole or in part. All authors have made substantial contributions to the study, have read and approved the final version of the manuscript, and agree to its submission for publication.
- The authors further declare that there are no financial, personal, professional, or institutional conflicts of interest that could have influenced the conduct, analysis, interpretation, or reporting of this research.

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