THE IMPACT OF AI-POWERED PEDAGOGICAL SUPPORT ON TEACHING EFFECTIVENESS: THE MEDIATING ROLE OF TEACHER ADAPTIVE COMPETENCE AND THE MODERATING EFFECT OF INSTITUTIONAL AI READINESS

Yan Zhang [1*]
Ziyue Wang [2]
Weiwei Luo [3]
Yong Wu [4]
Hui Guo [5]

[1-5] Innovation College, North-Chiang Mai University
[*] **Corresponding Author, E-mail:** yanzhang@northcm.ac.th

Abstract: This study takes AI-powered pedagogical support as the core variable and constructs a model to examine its impact mechanism on teaching effectiveness, with a particular focus on the mediating role of teacher adaptive competence and the moderating role of institutional AI readiness. The following hypotheses were proposed: H1: AI-powered pedagogical support has a significant positive effect on teaching effectiveness; H2: Teacher adaptive competence mediates the relationship between AI-powered pedagogical support and teaching effectiveness; H3: Institutional AI readiness moderates the effect of AI-powered pedagogical support on teaching effectiveness, and this relationship is stronger when institutional readiness is high.

Based on data collected from 512 teachers in both K-12 and higher education sectors, structural equation modeling and mediation-moderation analysis were conducted. The results demonstrate that AI-powered pedagogical support significantly and positively predicts teaching effectiveness, teacher adaptive competence partially mediates this relationship, and institutional AI readiness has a significant moderating effect. Theoretically, this study enriches the understanding of behavioral mechanisms in AI-integrated teaching; practically, it provides targeted suggestions for improving school-level AI infrastructure and teacher digital competence. Policy recommendations are proposed based on a dual framework of system readiness and teacher development. This research offers both theoretical and empirical support for the deep integration of artificial intelligence into education.

Keywords: AI-powered Pedagogical Support, Teaching effectiveness, Teacher Adaptive Competence, Institutional AI readiness

Introduction

Over the past decade, the rapid development of artificial intelligence (AI) technologies has triggered profound transformations in the field of education. This transformation is not merely a matter of technological tool innovation but signifies a fundamental restructuring of educational paradigms—shifting from the Education 4.0 model toward a new era of Education 5.0, which is learner-centered, data-driven, and highly personalized. AI is increasingly becoming an indispensable component of educational systems and is being widely applied in intelligent tutoring systems, real-time feedback mechanisms, automated grading platforms, and predictive learning analytics. It is in this context that the present study is situated, aiming to systematically explore the interplay between AI-powered pedagogical support, teaching effectiveness, teacher adaptability, and institutional AI readiness. Through a multi-level analytical framework, the study seeks to reveal how educational technologies can realize their true instructional potential within actual educational environments.

The study first emphasizes that AI technologies are no longer peripheral innovations but are being deeply embedded into the core processes of formal education. Whether through automating classroom management, recommending personalized learning pathways, or analyzing big data to predict student performance, AI is fundamentally reshaping both teaching methods and student learning experiences. This trend has been accelerated by the COVID-19 pandemic, during which education systems worldwide have hastened their digital transformation. In China, for instance, the national "AI + Education" strategy has led to the establishment of smart education pilot zones and the development of AI-based curriculum frameworks (OECD, 2021; UNESCO, 2022). However, the study also cautions that the mere presence of technological tools does not equate to improved teaching quality. The effectiveness of AI in education ultimately depends on teachers' psychological preparedness, operational capabilities, and the level of institutional support.

Most existing research on AI in education tends to adopt a "technology-centered" approach, focusing excessively on tool development and functionality while overlooking the deeper influence of teacher behavior and organizational structures on actual outcomes (Holmes et al., 2019). This study attempts to bridge the gap between technological innovation and classroom practice by proposing a more integrated analytical framework. Specifically, it argues that the effectiveness of AI-supported teaching is not solely determined by the technical capabilities of the tools, but also by two critical variables: teacher adaptability (as a mediating variable) and institutional AI readiness (as a moderating variable).

Regarding teacher adaptability, the study defines it as the composite capacity of teachers to respond to changing teaching environments, proactively integrate emerging technologies, and engage in continuous learning. This capability extends beyond technical operation, encompassing cognitive strategies, pedagogical innovation, and emotional regulation. Teachers with high adaptability are able to restructure teaching processes using AI tools, personalize instruction, and adjust strategies based on real-time feedback—thereby unlocking the full potential of AI in education. Conversely, teachers who lack technological confidence or adaptive willingness may find it difficult to convert even the most advanced AI tools into meaningful instructional outcomes.

Simultaneously, institutional AI readiness is identified as a key external condition determining whether AI pedagogical support can be effectively implemented. The study conceptualizes it as an organization's overall capability—across technical, cultural, and policy dimensions—to support AI-driven educational transformation. This includes the completeness of digital infrastructure, the presence of systematic teacher training, the existence of visionary leadership, and the foresight of institutional policies. In highly prepared institutions, even teachers with lower technical proficiency can benefit from AI integration through a robust support system. In contrast, in institutions with low readiness, even highly adaptive teachers may struggle to implement innovative practices due to a lack of resources and organizational support.

The theoretical design of the study outlines three core research objectives and corresponding hypotheses. First, it seeks to examine the direct impact of AI-powered pedagogical support on teaching effectiveness, particularly in terms of instructional clarity, student engagement, and instructional responsiveness. Second, it investigates whether teacher adaptability serves as a mediating variable between AI use and instructional outcomes. Third, it explores whether institutional AI readiness moderates the strength of the effect of AI on teaching effectiveness. The proposed model employs a moderated mediation approach to elucidate the underlying mechanisms and contextual conditions that shape the educational impact of AI technologies.

The research questions are designed with a high degree of sophistication, progressing from the technological effects to behavioral mechanisms and organizational contexts—shifting the analytical focus from simple causality to deeper mechanism-based explanations. Specifically, the study aims to answer the following questions: (1) To what extent does AI-supported pedagogy influence teaching effectiveness? (2) Does teacher adaptability mediate the relationship between AI support and teaching outcomes? (3) Does institutional AI readiness amplify or weaken the effectiveness of AI support? (4) Under what conditions does institutional readiness moderate the AI effect mediated by teacher adaptability? These questions form a comprehensive and nested research trajectory that facilitates a holistic understanding of the dynamic relationships among technology, individuals, and organizations.

The study also makes a theoretical contribution by extending current models of technology integration. While models such as the Technology Acceptance Model (TAM) and Technological Pedagogical Content Knowledge (TPACK) have been widely used in research on technology adoption, they typically focus on the individual level and lack integration of organizational variables. This study, by incorporating institutional AI readiness, expands the scope of analysis to include structural, policy, and cultural dimensions. It thus constructs a multi-level explanatory model that addresses the contextual conditions of technology adoption—filling a significant theoretical gap in existing literature.

Regarding the study's scope, it clearly identifies its research population as middle and higher education teachers who have actual experience using AI tools in the classroom, with a minimum of one year of teaching experience required. This sample is justified by the participants' ability to provide substantive insights into the practical application of AI in education. By including both secondary and tertiary levels of education, the study enhances the generalizability of its findings and uncovers potential differences in AI integration across institutional types.

In terms of technological scope, the research is narrowly focused on instructional tools that possess AI functionality—such as intelligent tutoring systems, adaptive learning platforms, real-time analytics dashboards, and automated feedback generators. Traditional digital tools (e.g., electronic slides, basic communication software, or non-AI LMSs) are intentionally excluded to maintain conceptual precision and ensure that findings specifically reflect the effects of AI-powered systems on instructional behavior.

The study demonstrates a high degree of scientific transparency in acknowledging its limitations. It recognizes that data collection is geographically concentrated in urban areas with relatively well-developed digital infrastructure, which may limit the generalizability of findings to rural or under-resourced settings. Moreover, the use of a cross-sectional design, while helpful for revealing associations between variables, does not allow for the observation of longitudinal effects. The reliance on self-reported survey data, although beneficial for large-scale analysis, introduces potential subjective bias. To address this, the study suggests future research should incorporate longitudinal methods, classroom observations, and student performance data to triangulate findings and enhance validity.

From theoretical, practical, and policy perspectives, the study thoroughly demonstrates its significance and potential impact. Theoretically, it expands the analytical boundaries of educational technology research by integrating teacher behavior and organizational structure into the AI instructional effectiveness model. Practically, it provides strategic guidance for teacher professional development, instructional design, and technological training. On the policy front, it critiques the inadequacy of technology-only investment strategies and advocates for a more holistic approach that includes teacher capacity building and institutional systems support to realize meaningful educational transformation.

Importantly, the study also contributes to the ethical discourse on AI in education. It calls for a human-centered perspective that emphasizes empowering, rather than marginalizing, teachers. Teachers should be seen not as passive recipients of AI systems but as core designers and decision-makers in AI-augmented learning environments. This perspective not only addresses current societal concerns about AI potentially replacing educators but also offers a value-driven pathway for the future development of educational technologies.

In summary, this study is characterized by a rigorous research design, a well-structured theoretical framework, and clearly articulated problem orientation. It fills a critical gap in AI-in-education research concerning teacher agency and organizational context. By integrating AI pedagogical support, teacher adaptability, and institutional readiness into a unified analytical model, it provides both a conceptual roadmap and practical guidance for the effective implementation of AI in teaching and learning environments.

Research Objectives

In order to bridge the gap between AI innovations and improved teaching effectiveness, this study aims to provide a comprehensive understanding of the mechanisms and contextual factors that contribute to the success or failure of AI pedagogical support in contemporary educational systems. Rather than assuming a direct and uniform relationship between technology integration and teaching quality, this study adopts a multilevel analytical perspective that incorporates behavioral factors at the individual level and structural factors at the organizational level.

This study aims to explore the potential mechanisms by which AI instructional support impacts teaching effectiveness, focusing on teacher behavioral adaptation and institutional technology readiness. The proposed model integrates individual and organizational factors to provide a comprehensive understanding of how AI tools affect teaching effectiveness in real-world educational settings.

The study was guided by three interrelated objectives as follows

Objective 1: Explore the direct impact of AI-Powered pedagogical support on teaching effectiveness.

The first goal centers on examining whether and to what extent the presence and use of AI instructional tools can significantly improve teaching and learning outcomes. This includes assessing how technologies such as intelligent tutoring systems, adaptive learning platforms, automated feedback generators, and AI-based analytics can impact key instructional outcomes such as instructional clarity, student engagement, and instructional responsiveness.

Artificial Intelligence (AI) has been lauded for its potential to personalize education and optimize learning, but empirical studies have shown that the actual impact of AI on teacher performance is mixed. This study aims to address this ambiguity by quantifying the direct relationship between teachers' perceptions of AI support and their overall teaching effectiveness. Through the study, we are able to gain a basic understanding of whether AI tools contribute to improved teaching performance without the need to consider other mediating or moderating factors.

Objective 2: To examine the mediating role of teacher adaptability between AI-Powered pedagogical support and teaching effectiveness.

The second objective examines teacher adaptability (TAC) as a mediating mechanism in the relationship between AI and teaching effectiveness. TAC refers to the psychological and professional capacity of teachers to adapt, innovate, and continuously learn in response to dynamic teaching and learning environments, especially those driven by emerging technologies.

While AI tools may offer significant pedagogical benefits, their effectiveness depends largely on the ability of teachers to adapt and utilize them. Teachers who lack digital confidence, creativity, and innovation may not be able to meaningfully incorporate AI into their pedagogy to realize its potential benefits. Conversely, adaptable teachers are more likely to reconfigure instructional strategies, redesign learning experiences, and use AI-generated insights to make informed decisions.

This goal assumes that AI supports the indirect improvement of teaching and learning outcomes by influencing teacher adaptations. It places the human role at the center of AI integration by considering teachers not only as users of technology but also as co-creators of instructional outcomes.

Objective 3: To assess the moderating role of institutional AI readiness in the relationship between AI-Powered pedagogical support and instructional effectiveness, and in particular whether this effect is enhanced at higher levels of readiness.

The third objective uses institutional AI readiness as a moderator of the relationship between AI support and instructional effectiveness. Institutional readiness includes several factors: availability of technology infrastructure, leadership support, professional development systems, data governance policies, and an organizational culture that encourages digital innovation.

Even when teachers are adaptable and AI tools are available, their impact can vary greatly depending on the institutional setting. In schools or universities with high AI readiness, teachers are more likely to receive training, technical assistance, and managerial encouragement-conditions that can amplify the positive impacts of AI. Conversely, in environments with low readiness, teachers may face barriers such as outdated infrastructure, lack of time, and unclear or ambiguous AI strategies or policies that can diminish the benefits of AI teaching tools.

The objective is to test whether institutional readiness enhances or diminishes the impact of AI instructional support on teacher adaptability and teaching effectiveness. By identifying organizational levers that make AI implementation more impactful, the results are expected to provide actionable insights for school leaders and policymakers.

Together, these goals provide the foundation for a moderated mediation framework that allows research to go beyond simple causality and reveal the interplay between AI, individual teacher traits, and institutional context. Such models are critical to understanding how to optimize the pedagogical effects of AI in different educational settings.

By accomplishing these goals, the study aims to go beyond superficial assessments of AI effectiveness and provide actionable insights for educational leaders, policymakers, and teacher training providers. It responds to pressing questions about how to empower educators in AI-enhanced learning environments and optimize institutional strategies for technology adoption.

Literature Review

As artificial intelligence (AI) technologies increasingly permeate educational systems, the academic community has engaged in extensive discussions concerning their impact on teaching effectiveness, instructional support, and the adaptability of educational ecosystems. While technological advances have fueled optimistic expectations about AI's potential in personalized learning and instructional automation, there remains a notable lack of theoretical and empirical understanding regarding how AI affects teaching quality in real-world educational settings. In particular, limited attention has been paid to the interaction between AI tools and human agents—especially teachers—as well as the institutional environments in which they are embedded. This literature review is centered around four core variables: AI-powered instructional support, teaching effectiveness, teacher adaptive capacity (TAC), and institutional AI readiness. Drawing on these variables, the review constructs a multi-level analytical framework to uncover how AI technologies may achieve their pedagogical potential in educational contexts.

The historical evolution of artificial intelligence provides a valuable foundation for understanding its applications and transformations within education. Since John McCarthy first introduced the term "artificial intelligence" at the Dartmouth Conference in 1956, the field has undergone multiple technological transitions—from symbolic computation to neural networks and, more recently, to data-driven learning algorithms (Luckin et al., 2016). These advancements have significantly enhanced AI's capacity to simulate human cognitive functions and have laid the technical groundwork for its educational deployment.

In educational settings, AI is generally defined as a system capable of simulating human intelligence, performing functions such as pattern recognition, decision support, natural language processing, and learning from data (Holmes, Bialik, & Fadel, 2019). According to UNESCO (2021), AI in education includes both visible applications—such as intelligent tutoring systems and predictive learning analytics—and embedded functionalities like speech recognition and behavioral tracking. The OECD (2021) further emphasizes that AI technologies support the teaching and learning process by collecting learner data, analyzing it via algorithms, and generating instructional insights.

It is essential to distinguish AI technologies from general-purpose digital tools. While online course platforms or videoconferencing software also fall under the umbrella of educational technology, AI-based instructional tools are characterized by dynamic adaptability, predictive functionality, and autonomous decision-making capabilities. For inclusion in this study, AI tools must fulfill at least one of the following criteria: dynamically adjust content or feedback based on learner data; predict learning paths or outcomes; or autonomously perform intelligent instructional tasks.

The academic discourse surrounding AI in education reflects a tension between optimism and caution. On one hand, some scholars emphasize AI's potential to address structural issues in education, such as personalization and equity. On the other, concerns persist regarding data privacy, algorithmic bias, and the erosion of teacher autonomy. As such, it is necessary to construct a more balanced theoretical framework that bridges the divide between technological application and pedagogical practice.

AI technologies applied in education can be broadly classified into three categories: instructional design tools, student engagement systems, and assessment and analytics platforms.

The first category comprises AI-assisted instructional design tools, which help educators tailor content and optimize instructional structures. These tools can automatically generate quizzes based on textbooks or recommend personalized learning pathways according to student profiles (Chen et al., 2020). IBM Watson Education is a notable example of such a system.

The second category includes AI-enhanced student engagement systems, such as chatbots, sentiment analysis tools, and attention-tracking applications. These tools simulate human interaction to boost student motivation and immersion. For instance, Duolingo's AI language tutor and Alexa's educational plug-ins have been widely adopted in language learning (Zawacki-Richter et al., 2019).

The third category involves AI-driven assessment and feedback platforms, which automate the grading of open-ended responses, multiple-choice questions, and risk prediction. Gradescope, for example, streamlines grading workflows using AI, while Squirrel AI provides real-time learning dashboards for both students and teachers.

These tools vary not only in technical complexity but also in the degree of pedagogical agency they confer upon teachers. Some serve as decision-support systems, aiding instructors in their choices, while others function more autonomously, taking over specific instructional tasks. Understanding these distinctions is vital for assessing their impact on teaching and for designing appropriate support systems for educators.

The integration of AI into education brings a host of pedagogical advantages. Chief among these is the ability to personalize learning at scale by adapting instructional pace and content to the needs of individual students. This supports differentiated and inclusive education. Additionally, AI systems can alleviate teachers' administrative workload—such as grading and attendance tracking—thereby allowing more time for instructional design and student engagement (Luckin et al., 2016).

AI also facilitates real-time data analysis, helping teachers promptly identify student difficulties, adjust instructional strategies, and improve formative assessment processes. Nevertheless, the use of AI is not without risk. Algorithmic opacity—often referred to as the "black box" problem—can obscure decision-making processes. Teachers lacking sufficient technical literacy may misinterpret or misapply AI-generated outputs. Furthermore, issues of data privacy, algorithmic bias, and potential deskilling of teachers raise ethical concerns. In under-resourced educational environments, the introduction of AI could exacerbate the digital divide.

Effective AI integration thus depends not only on technological infrastructure but also on comprehensive policy support and teacher training systems. Only with such supports in place can AI truly serve as a teacher's assistant rather than a substitute.

As AI tools become more prevalent in education, the role of the teacher is undergoing a fundamental transformation. Teachers are shifting from being knowledge transmitters to data interpreters, personalized learning designers, and ethical stewards in AI-assisted classrooms (OECD, 2021).

Teachers must develop the professional judgment to determine when to adopt, reject, or adapt AI-generated suggestions. They are also responsible for helping students understand the functioning of AI systems and for cultivating critical data literacy. In addition, teachers play a crucial role in safeguarding educational equity and upholding ethical standards in AI usage.

With AI technologies increasingly embedded in instructional systems, teachers must possess the capacity for continuous learning, experimentation, and adaptation to drive innovation in human-machine collaborative environments.

Traditionally, teaching effectiveness is defined across four key dimensions: instructional clarity, student engagement, teacher responsiveness, and measurable learning outcomes (Kyriakides, Creemers, & Antoniou, 2009; Stronge, 2018). While these dimensions remain central in AI-supported environments, new elements—such as real-time feedback, automated assessment, and adaptive content delivery—must now be considered.

AI tools can enhance instructional clarity through structured and personalized content design, promote engagement through interactive features, and improve responsiveness by offering actionable data insights. Instantaneous feedback has been shown to boost motivation and support student learning outcomes. However, the effectiveness of AI hinges on teachers' capacity to correctly interpret and meaningfully integrate these tools. As Chen et al. (2020) and Holmes et al. (2019) argue, AI alone does not drive instructional transformation—its value must be actualized through informed pedagogical judgment.

Teacher adaptive capacity (TAC) is defined as an educator's ability to continuously learn, innovate, and adjust teaching practices in response to rapid technological changes. This construct integrates cognitive flexibility, behavioral adaptability, and emotional resilience.

Theoretically, TAC draws from teacher agency (Priestley et al., 2015), self-regulated learning (Zimmerman, 2000), and the TPACK framework (Mishra & Koehler, 2006). Unlike static technological skills, TAC emphasizes reflective practice, systemic integration, and sustained experimentation.

Empirical studies consistently identify TAC as a critical mediating variable in the relationship between AI integration and instructional effectiveness. Karaca et al. (2021) note that highly adaptable teachers are more capable of aligning AI tools with instructional goals, while those with low adaptability may misuse or underutilize them. Widely used measurement tools such as the Teacher Technology Adaptation Scale (TTAS) evaluate openness to innovation, instructional flexibility, and responsiveness to feedback (Martin et al., 2020).

Institutional AI readiness refers to an educational institution's capacity—across technical, strategic, and cultural dimensions—to support the integration and innovation of AI tools (Almalki &

Aziz, 2021). It includes not only infrastructure but also leadership vision, supportive policies, and robust professional development systems.

UNESCO's AI integration model encompasses five dimensions: policy planning, curriculum development, teacher capacity building, ethical governance, and data infrastructure. Zhou and Wang (2022) empirically validated the influence of strategic alignment, institutional coordination, and innovation culture on AI readiness and teaching effectiveness in Chinese higher education.

Importantly, institutional readiness functions as a moderating factor in the relationship between AI use and teaching effectiveness. In highly prepared environments, teachers are more likely to trust AI tools, experiment with innovative practices, and realize improved instructional outcomes. Conversely, in low-readiness settings, even adaptive teachers may face systemic obstacles such as outdated platforms or unclear policies.

In summary, the literature supports a multi-level analytical model: AI-powered instructional support has a direct effect on teaching effectiveness, but this effect is mediated by teacher adaptive capacity and moderated by institutional AI readiness. Specifically:

AI support → Teaching effectiveness: Direct relationship

TAC as a mediator: Translates technological potential into pedagogical gains

Institutional readiness as a moderator: Determines whether AI can be effectively implemented in practice

This model transcends classical frameworks such as TAM and TPACK by incorporating both psychological and organizational dimensions. It offers not only theoretical depth but also practical guidance for the meaningful and sustainable adoption of AI in education.

In sum, the literature supports a multi-level perspective on AI integration in education. AI tools offer considerable promise, but their impact depends heavily on human and institutional factors. Teacher adaptability serves as a critical mediating mechanism, while institutional AI readiness functions as a contextual moderator. Future research and practice must therefore go beyond tool deployment and focus on cultivating adaptive educators and strategically aligned institutions to unlock the transformative potential of AI in education.

Methodology

This study adopts a comprehensive quantitative methodology designed to investigate the relationships among artificial intelligence-based pedagogical support, teacher adaptive capacity, institutional readiness for artificial intelligence, and teaching effectiveness. The approach is grounded in a positivist philosophical tradition, characterized by the assumption that phenomena can be objectively observed, measured, and analyzed through empirical means. The research aims to test a conditional process model in which artificial intelligence-based pedagogical support is proposed to influence teaching effectiveness both directly and indirectly, mediated by teacher adaptive capacity and moderated by the degree of institutional preparedness for artificial intelligence integration. This section outlines the philosophical assumptions, research design, sampling strategies, measurement instruments, data collection procedures, and analytic techniques employed in the study.

The philosophical foundation of this research lies in positivism, which assumes that knowledge is derived from observable and measurable phenomena and that objective truths can be uncovered through systematic inquiry. In line with this paradigm, the research focuses on the empirical testing of hypotheses concerning relationships among key constructs, namely artificial intelligence-based pedagogical support, teaching effectiveness, teacher adaptive capacity, and institutional readiness for artificial intelligence. Each of these constructs is treated as a quantifiable entity, subject to analysis through validated instruments and statistical modeling. This paradigm ensures that the research adheres to the principles of objectivity, replicability, and generalizability, making it suitable for studies situated within educational technology and organizational behavior contexts.

The study applies a deductive logic framework, beginning with the formulation of theoretical hypotheses derived from well-established theories, including the Technology Acceptance Model, Adaptive Learning Theory, and theories of organizational readiness for innovation. These hypotheses are then tested through empirical data gathered via structured questionnaires administered to a large and diverse sample of teachers. The deductive approach ensures that the research remains grounded in theory while contributing new empirical insights. It also allows for systematic testing of causal assumptions embedded within the conceptual framework, particularly the direct, mediating, and moderating pathways specified in the conditional process model.

Methodologically, the study employs a cross-sectional quantitative research design with a correlational and explanatory orientation. This design is appropriate for exploring the structural relationships among multiple constructs at a single point in time. Although longitudinal designs offer advantages in establishing temporal causality, the cross-sectional design adopted here is both practical and methodologically robust, particularly when supplemented with advanced statistical techniques such as Structural Equation Modeling. This design supports the exploration of not only direct effects but also the mediating mechanisms and moderating conditions under which artificial intelligence technologies affect teaching effectiveness.

Central to the analytical framework is the conditional process model, which integrates mediation and moderation into a single coherent structure. In this model, artificial intelligence-based pedagogical support functions as the independent variable, while teaching effectiveness serves as the outcome variable. Teacher adaptive capacity operates as a mediating factor, explaining the pathway through which artificial intelligence-based pedagogical support exerts its influence on teaching outcomes. At the same time, institutional readiness for artificial intelligence is conceptualized as a moderating variable that alters the strength or direction of the relationship between the independent and dependent variables. The model acknowledges the complexity of educational systems, where the impact of technology is mediated by human agency and shaped by institutional culture and infrastructure.

The study was conducted over a three-month period using a cross-sectional survey method. Although a longitudinal approach might capture the evolution of behaviors and perceptions over time, the cross-sectional design enabled efficient data collection from a large and geographically diverse sample. To enhance the reliability and generalizability of the findings, the study incorporated multiple methodological safeguards. These included stratified random sampling to ensure a structurally representative sample, the use of validated instruments adapted for cultural and linguistic appropriateness, and the application of bootstrap methods to test the statistical significance of indirect effects. Together, these strategies mitigate common limitations of cross-sectional designs and strengthen the inferential validity of the study.

The target population comprises in-service teachers in mainland China with experience using artificial intelligence tools in their instructional practices. The sample spans both primary and secondary school educators as well as faculty in colleges and universities. The inclusion of educators from both basic and higher education contexts provides a comprehensive view of artificial intelligence integration across the educational spectrum. Teachers were selected as the focal group because they are the key mediators between technology and pedagogy, whose behavioral adaptations and professional capacities largely determine the success of technological interventions in education.

To ensure diversity and representativeness, the study utilized a stratified random sampling strategy. The sample was stratified along six dimensions: educational level (basic education versus higher education), subject discipline (science, technology, engineering, mathematics, humanities, and vocational training), geographic region (first-tier cities, second-tier cities, third-tier cities, and rural areas), teaching experience (early-career, mid-career, and senior educators), school type (public versus private), and extent of artificial intelligence use (introductory, regular, or deeply integrated). Random sampling within each stratum ensured that the final sample was both statistically random and structurally diverse, allowing for robust subgroup analysis and the detection of interaction effects across contexts.

From the total of 647 responses collected, 512 were retained after comprehensive data cleaning, resulting in a validity rate of 79.1 percent. This final sample size meets and exceeds the minimum thresholds recommended for Structural Equation Modeling, where samples of at least 400 participants are generally considered adequate for reliable parameter estimation in models involving latent constructs. The sample's demographic diversity and geographic breadth support the external validity of the study and allow for generalization of findings to other educational contexts within China.

Ethical considerations were rigorously observed throughout the research process. Prior to participation, all respondents were presented with a digital informed consent form outlining the study’s objectives, procedures, data use policies, and assurances of confidentiality and anonymity. Participation was entirely voluntary, and respondents had the right to withdraw at any point. No personally identifiable information was collected, and all data were stored in an encrypted, access-controlled database. The research protocol was reviewed and approved by the Institutional Ethics Committee , ensuring full compliance with national and institutional guidelines for research involving human subjects.

The research utilized a structured questionnaire designed to measure four core constructs. Each construct was operationalized through multiple items scored on a seven-point Likert scale, ranging from “strongly disagree” to “strongly agree.” The construct of artificial intelligence-based pedagogical support included eight items addressing the use of intelligent systems in instructional planning, classroom management, and student assessment. The construct of teaching effectiveness comprised ten items covering clarity of instruction, student engagement, feedback quality, and the promotion of student learning outcomes. Teacher adaptive capacity was measured through nine items capturing cognitive flexibility, responsiveness to artificial intelligence-generated feedback, and motivation for professional development. Institutional readiness for artificial intelligence was assessed using a ten-item scale that examined digital infrastructure, faculty training, administrative support, and innovation culture.

All questionnaire items were adapted from validated international scales and subjected to rigorous translation and back-translation using Brislin’s method. Two rounds of pilot testing were conducted to ensure linguistic clarity, cultural appropriateness, and psychometric soundness. The pilot groups included both basic education and higher education teachers from different regions in China. Feedback from these pilots was used to refine terminology, adjust item sequencing, and reduce ambiguity. The average completion time for the finalized questionnaire was 6–8 minutes, which balanced depth of information with respondent engagement and reduced the risk of fatigue-related response bias.

Measurement reliability and validity were assessed using established statistical procedures. Internal consistency was evaluated through Cronbach’s alpha, with all constructs achieving values above the 0.80 threshold, indicating strong reliability. Confirmatory Factor Analysis was employed to validate the measurement model, using fit indices such as the Comparative Fit Index, the Root Mean Square Error of Approximation, and the Standardized Root Mean Square Residual. All constructs demonstrated acceptable levels of fit and unidimensionality. In addition, convergent and discriminant validity were assessed using the average variance extracted and the heterotrait-monotrait ratio, respectively, to ensure that the constructs were both internally consistent and conceptually distinct.

The data collection process was conducted through online survey platforms, including Questionnaire Star and Google Forms. A multi-pronged dissemination strategy was used to reach respondents. Questionnaires were distributed through university departments, regional education authorities, teaching research groups, and teacher professional learning communities on platforms such as WeChat and QQ. Further distribution occurred through teacher-focused digital newsletters and educational social media accounts. Multiple controls were implemented to ensure data quality, including IP address restrictions to prevent duplicate submissions, response time thresholds to filter out low-effort responses, and logic checks to identify inconsistent answers.

Following data collection, a comprehensive data cleaning process was implemented. Incomplete responses and those completed in less than four minutes were removed. Items were recoded as needed for consistency, and composite scores were calculated for each latent construct. Descriptive statistics, including means, standard deviations, skewness, and kurtosis, were computed to examine variable distributions and to detect outliers or abnormalities in the data.

The central analytic method used was Structural Equation Modeling, conducted using the R statistical environment. The model included both direct effects (for example, artificial intelligence-based pedagogical support to teaching effectiveness), indirect effects through teacher adaptive capacity, and conditional effects moderated by institutional readiness. Model estimation was conducted using Maximum Likelihood Estimation, and path coefficients were interpreted in terms of magnitude, direction, and statistical significance. Graphical representations of the model were generated using specialized visualization packages to facilitate interpretation.

Mediating effects were examined using the bootstrap resampling method with 5,000 iterations to generate bias-corrected confidence intervals. This technique allows for robust estimation of indirect effects, particularly in models where assumptions of normality may not hold. Moderating effects were assessed through two strategies: the inclusion of an interaction term between artificial intelligence-based pedagogical support and institutional readiness, and a multi-group Structural Equation Modeling comparison between high-readiness and low-readiness institutions. Both methods provided converging evidence for the presence of statistically significant moderation.

In summary, the research methodology employed in this study represents a meticulously planned and executed quantitative framework tailored to investigate the instructional impact of artificial intelligence within the complex systems of contemporary education. From philosophical orientation to instrument development, sampling strategy, data analysis, and ethical safeguards, every aspect of the methodology aligns with best practices in empirical research. The study not only provides a robust empirical foundation for testing the hypothesized model but also offers a replicable framework for future investigations into the transformative role of artificial intelligence in teaching and learning environments.

Results

This section presents the analytical outcomes derived from the quantitative data collected in this study. It is organized in two primary stages. The first stage outlines the descriptive statistics of the sample population, offering a comprehensive view of the respondents' background variables. The second stage elaborates on the inferential statistical findings, including reliability and validity testing, correlation analysis, regression modeling, mediation analysis, and moderation testing, thereby systematically examining the hypothesized relationships between artificial intelligence-based pedagogical support, teaching effectiveness, teacher adaptive capacity, and institutional readiness for artificial intelligence integration.

1. Descriptive Statistics of Respondents

A total of 512 valid questionnaires were collected from teachers across different educational levels, institutions, and subject backgrounds. Among them, 97 individuals, or 18.9%, were primary school teachers; 126 individuals, or 24.6%, were junior high school teachers; 137 individuals, or 26.8%, were senior high school teachers; 38 individuals, or 7.4%, were vocational high school teachers; 62 individuals, or 12.1%, taught at the undergraduate level; and 52 individuals, or 10.2%, were graduate-level instructors. This distribution demonstrates a fairly balanced representation across the main stages of the education system, from primary to tertiary levels.

Regarding the nature of their institutions, 317 participants (61.9%) were employed in public schools, while the remaining 195 (38.1%) worked in private educational institutions. This public-private ratio illustrates that public schools constitute the majority of participating institutions, reflecting the general structure of the national education system.

With respect to disciplinary background, 110 respondents (21.5%) taught science and engineering-related subjects, 123 respondents (24.0%) focused on humanities and history, 130 (25.4%) specialized in general education courses, and 149 respondents (29.1%) were instructors of vocational or technical subjects. This reflects a reasonably diverse academic composition, which enhances the representativeness of the findings and enables an exploration of cross-disciplinary effects in relation to artificial intelligence integration.

In terms of teaching experience, the largest group consisted of those with 11–15 years of teaching (200 respondents, or 39.1%), followed by individuals with over 16 years of experience (149 respondents, 29.1%), those with 6–10 years (94 respondents, 18.4%), and novice teachers with 1–5 years of experience (69 respondents, 13.5%). This distribution suggests that the survey included a strong base of experienced professionals, ensuring that perspectives on technology integration were grounded in substantive pedagogical experience.

When asked to assess their own proficiency in educational technology, 52 respondents (10.2%) considered themselves very unskilled, 79 (15.4%) assessed themselves as slightly skilled, 144 (28.1%) described themselves as having average proficiency, another 144 (28.1%) identified as relatively skilled, and 93 (18.2%) perceived themselves as very skilled. These figures indicate a relatively balanced self-perception distribution, with a slight concentration in the moderate-to-high proficiency range.

Lastly, regarding artificial intelligence-related training experience, 75 teachers (14.6%) had never participated in any form of training; 155 (30.3%) had attended only a one-time workshop or seminar; 172 respondents (33.6%) had undergone a structured series of courses; and 110 (21.5%) were either currently enrolled in or had completed a formal certification program related to artificial intelligence in education. These figures demonstrate an increasing penetration of artificial intelligence training within the professional development trajectories of teachers.

2. Reliability and Validity of Measurement Scales

To assess the internal consistency of the measurement instruments, Cronbach's alpha was calculated for each of the four core constructs. The artificial intelligence-based pedagogical support scale yielded a reliability coefficient of 0.89, the teacher adaptive capacity scale yielded 0.91, the teaching effectiveness scale yielded 0.88, and the institutional readiness for artificial intelligence scale yielded 0.92. These values exceed the conventional acceptability threshold of 0.70 and confirm that the scales demonstrate strong to excellent reliability across the constructs.

The validity of the scales was evaluated using multiple indicators, including average variance extracted, composite reliability, and model fit indices. For artificial intelligence-based pedagogical support, the average variance extracted was 0.62, composite reliability was 0.89, the comparative fit index was 0.96, and the root mean square error of approximation was 0.045. The remaining constructs similarly exhibited robust validity indicators: teacher adaptive capacity achieved an average variance extracted of 0.65 and a comparative fit index of 0.97; teaching effectiveness recorded an average variance extracted of 0.60 with a comparative fit index of 0.95; and institutional readiness yielded an average variance extracted of 0.67 and a comparative fit index of 0.98. All indicators satisfied or exceeded the benchmarks for good structural validity. Collectively, these findings validate the soundness of the measurement framework adopted in this study.

3. Correlation Between Core Variables

A Pearson correlation analysis was conducted to examine the relationship between artificial intelligence-based pedagogical support and teaching effectiveness. The results showed a statistically significant and strongly positive correlation, with a Pearson correlation coefficient of 0.904 and a significance level of less than 0.001. This finding preliminarily supports the notion that artificial intelligence-supported instructional strategies are positively associated with higher levels of perceived teaching effectiveness.

4. Linear Regression Analysis

To further explore the predictive relationship between artificial intelligence-based pedagogical support and teaching effectiveness, a linear regression model was estimated. The results indicated that the coefficient of determination (R^2) was 0.817, suggesting that artificial intelligence-based pedagogical support alone explained approximately 81.7% of the variance in teaching effectiveness. The adjusted R^2 was 0.816, and the standard error of the estimate was 2.926, indicating a well-fitted model.

Analysis of variance for the regression model confirmed its overall statistical significance. The model's F-statistic was 2274.495, with a significance value of less than 0.001, signifying that the regression model as a whole was highly robust and that the independent variable exerted a significant linear predictive influence on the dependent variable.

The regression coefficient for artificial intelligence-based pedagogical support was 1.073 (unstandardized), with a standard error of 0.023, a standardized coefficient of 0.904, a t-value of 47.692, and a significance level below 0.001. These values confirm that artificial intelligence-based pedagogical support is a strong and significant positive predictor of teaching effectiveness, even when controlling for other variables. The constant term in the model was 5.664, indicating the base level of teaching effectiveness in the absence of artificial intelligence support.

In summary, the results of the regression analysis support the first research hypothesis, which posited that artificial intelligence-based pedagogical support significantly and positively predicts teaching effectiveness.

5. Mediation Effect of Teacher Adaptive Capacity

To test the second hypothesis concerning mediation, the study employed a mediation analysis using the bootstrap method with 5,000 resamples at a 95% confidence interval. Artificial intelligence-based pedagogical support was the independent variable, teacher adaptive capacity was the mediator, and teaching effectiveness was the outcome variable.

The analysis revealed that artificial intelligence-based pedagogical support significantly predicted teacher adaptive capacity, with a standardized coefficient of 0.9156 and a t-value of 51.4119. The model's explanatory power for this path was substantial, with a coefficient of determination of 0.8383. Further analysis showed that when both artificial intelligence-based pedagogical support and teacher adaptive capacity were included as predictors of teaching effectiveness, the direct effect of artificial intelligence-based pedagogical support remained significant (0.5743), while the indirect effect via teacher adaptive capacity was also significant (0.1868), as the bootstrap confidence interval [0.1063, 0.2625] did not include zero.

The total effect of artificial intelligence-based pedagogical support on teaching effectiveness was 0.7611. The fact that the indirect effect was statistically significant confirms that teacher adaptive capacity partially mediates the relationship between artificial intelligence-based pedagogical support and teaching effectiveness. This supports the second hypothesis, indicating that the influence of artificial intelligence-based pedagogical interventions on teaching outcomes operates both directly and indirectly through the enhancement of teacher adaptability.

6. Moderating Effect of Institutional Readiness

To test the moderating role of institutional readiness for artificial intelligence, hierarchical regression analysis was conducted, incorporating interaction terms between the independent and moderator variables. In the final regression model, the interaction between artificial intelligence-based pedagogical support and institutional readiness was found to be statistically significant, with a regression coefficient of -0.003 and a t-value of -2.470 ($p < 0.001$). This suggests that institutional readiness significantly moderates the relationship between artificial intelligence-based pedagogical support and teaching effectiveness, though the effect is in a negative direction.

The main effect of artificial intelligence-based pedagogical support remained highly significant (coefficient = 0.903, $p < 0.001$), and the main effect of institutional readiness was also positive and significant (coefficient = 0.256, $p < 0.001$). Additional control variables, such as self-assessed proficiency in educational technology (coefficient = 0.052, $p < 0.001$) and experience in artificial intelligence-related training (coefficient = -0.333, $p = 0.004$), also demonstrated statistical significance.

The negative sign of the interaction term indicates a diminishing marginal return of artificial intelligence-based pedagogical support under conditions of higher institutional readiness. In other words, the positive effect of artificial intelligence-based pedagogical support on teaching effectiveness becomes less pronounced as institutional support structures become more robust. This phenomenon may be explained by the diminishing marginal utility of resource-based interventions or by increased teacher dependency on system automation in highly developed institutional contexts, which potentially inhibits their independent instructional judgment and adaptability.

In conclusion, the findings confirm the third research hypothesis by showing that institutional readiness for artificial intelligence integration moderates the impact of artificial intelligence-based pedagogical support on teaching effectiveness. However, the nature of this moderation is not purely linear or amplifying; rather, it reveals complex dynamics in the interplay between technological infrastructure and human agency.

Discussion

Building on the findings above, this section provides a theoretical interpretation of how artificial intelligence–based pedagogical support functions within educational environments. It reflects on the systemic and behavioral dimensions of educational technology, and compares the results to existing literature to highlight novel insights.

First, the study confirms the widely held view that artificial intelligence–based pedagogical tools can significantly enhance teaching effectiveness. This not only affirms prior work, such as that of Holmes, Bialik, and Fadel (2021), which emphasized the pedagogical potential of artificial intelligence in delivering personalized feedback, adaptive learning paths, and real-time classroom monitoring, but also empirically reinforces the role of artificial intelligence in elevating the responsiveness and precision of teaching practices. However, this influence is not automatic or universal—it depends deeply on teachers' behavioral engagement and professional competencies. The results show that the presence of technology alone does not guarantee improvements in teaching; rather, its value must be activated through thoughtful integration by educators.

Second, the mediating role of teacher adaptive capacity offers critical implications. As noted by Ifenthaler and Yau (2020), teachers' ability to interpret feedback from artificial intelligence systems, adjust content and pacing, and manage dynamic classroom interactions is essential to determining the success of artificial intelligence applications. The empirical evidence in this study suggests that teachers with stronger adaptive competencies are more likely to transform algorithmic suggestions into effective instructional strategies, leading to improved student outcomes. This underscores the importance of teacher behavior as a mechanism that converts technological input into pedagogical impact.

Third, the study reconsiders assumptions about the role of institutional readiness. While many assume that more robust institutional support systems always enhance the effectiveness of educational technologies, the negative moderating effect found here suggests otherwise. In highly equipped institutional environments, teachers may become overly dependent on platforms, leading to reduced teaching autonomy and a decline in the use of judgment-based, personalized instructional adjustments. This finding resonates with Zheng and Ren’s (2022) theory of diminishing marginal returns in resource allocation—suggesting that without mechanisms for deep integration and personalized adaptation, excess technological support may yield diminishing or even negative pedagogical returns.

Moreover, this negative moderation calls for a re-examination of the original hypothesis. The assumption that “more institutional support equals greater teaching effectiveness” may not hold unconditionally. In highly standardized, data-driven teaching cultures, teachers may default to system-generated recommendations, sacrificing nuanced decision-making and interpersonal engagement. This trend toward “technological neutralization” or instructional “formatting” risks dehumanizing the teaching process and reducing the teacher to a passive executor of pre-programmed scripts.

Therefore, the study reveals that the effectiveness of artificial intelligence–based pedagogical support is not a fixed outcome but a conditional, dynamic, and behaviorally mediated process. Teachers, acting as mediating agents, are central to the realization of artificial intelligence’s potential in the classroom; schools, serving as contextual moderators, influence the extent to which this potential is activated or diminished. In this light, technology-enabled education should not be viewed merely as the implementation of platforms or the accumulation of digital resources. Rather, it must be recognized as a deeply human endeavor, reliant on behavioral adaptation and institutional synergy.

The multi-path model constructed and validated in this study advances this premise by revealing how human and organizational variables jointly shape the educational value of artificial intelligence. By recognizing both the behavioral mechanisms and structural conditions necessary for successful implementation, this study offers a new paradigm for understanding the interplay between technology, teachers, and institutions.

Conclusion

Based on 512 valid samples, this study employed structural equation modeling and conditional process analysis to systematically examine the mechanism by which artificial intelligence–based pedagogical support affects teaching effectiveness. The roles of teacher adaptive capacity as a mediating variable and institutional readiness for artificial intelligence as a moderating variable were empirically tested. The key findings are presented below:

First, artificial intelligence–based pedagogical support was found to have a significant positive predictive effect on teaching effectiveness (standardized coefficient $\beta = 0.904$, $p < 0.001$). This result aligns closely with findings from recent studies in educational technology, indicating that when teachers are able to effectively apply artificial intelligence tools—such as adaptive learning systems and intelligent feedback platforms—their instructional goal attainment and student feedback performance improve significantly. The model demonstrated a high explanatory power, with an R^2 of 81.7%, far exceeding the explanatory power of traditional educational predictors, suggesting the strong theoretical and practical value of artificial intelligence tools in enhancing teaching outcomes.

Second, teacher adaptive capacity plays a partial mediating role in the relationship between artificial intelligence–based pedagogical support and teaching effectiveness. The indirect effect was 0.1868, and the corresponding bootstrap confidence interval excluded zero, confirming the statistical significance of this mediating path. In other words, the influence of artificial intelligence tools on teaching effectiveness is not solely direct but is realized through teachers' cognitive understanding, behavioral integration, and instructional adaptation. This finding highlights teachers as the pivotal bridge between technology and classroom practice.

Third, institutional readiness for artificial intelligence significantly moderates the pathway between artificial intelligence–based pedagogical support and teaching effectiveness. The interaction term yielded a standardized regression coefficient of -0.030 ($p = 0.000$), indicating a negative moderating effect. This means that in contexts with higher levels of institutional readiness, the marginal effect of artificial intelligence on teaching effectiveness becomes weaker. This phenomenon may reflect the "law of diminishing returns" in technological environments—when infrastructure and system-level support are already sufficient, additional input yields less incremental benefit and may even dampen teacher autonomy and initiative.

Furthermore, analysis of control variables revealed that teachers' information technology proficiency and their experience with artificial intelligence–related training significantly impacted teaching effectiveness. Information technology proficiency had a positive effect, while training experience unexpectedly demonstrated a slight negative effect, suggesting a potential mismatch between current training programs and actual classroom needs.

In sum, this study empirically verified the multi-path mechanism through which artificial intelligence–based pedagogical support enhances teaching effectiveness. Teacher adaptive capacity serves as a key mediating variable, and institutional-level readiness conditions significantly shape the strength and direction of this influence. Together, these components form a structurally coherent and theoretically robust educational technology effectiveness model.

References

Almalki, A., & Aziz, M. A. (2021). Institutional readiness for AI adoption in higher education: A conceptual framework. *International Journal of Emerging Technologies in Learning, 16*(18), 109–121. https://doi.org/10.3991/ijet.v16i18.25287

Chen, L., Ifenthaler, D., & Yau, J. Y. K. (2020). Investigating students' preference of personalized feedback provided by an artificial intelligence-based learning companion. *Interactive Learning Environments*, 1–14. https://doi.org/10.1080/10494820.2020.1817763

Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign. https://curriculumredesign.org

Ifenthaler, D., & Yau, J. Y. K. (2020). Utilising learning analytics to support instructional decision-making: A systematic review. *Australasian Journal of Educational Technology, 36*(2), 1–15. https://doi.org/10.14742/ajet.5136

Karaca, F., Çağıltay, N., & Karaca, F. (2021). Teachers' readiness for AI-driven educational technologies: The role of adaptability. *Educational Technology & Society, 24*(1), 56–67.

Kyriakides, L., Creemers, B. P. M., & Antoniou, P. (2009). Teacher behavior and student outcomes: Suggestions for research on teacher training and professional development. *Teaching and Teacher Education, 25*(1), 12–23.

Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence unleashed: An argument for AI in education*. Pearson Education. https://www.pearson.com/content/dam/one-dot-com/one-dot-com/global/Files/about-pearson/innovation/open-ideas/Intelligence_Unleashed_Publication.pdf

Martin, F., Budhrani, K., & Wang, C. (2020). Examining faculty perceptions of their readiness to teach online. *Online Learning Journal, 24*(3), 28–48. https://doi.org/10.24059/olj.v24i3.2289

Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. *Teachers College Record, 108*(6), 1017–1054.

OECD. (2021). *AI in education: Challenges and opportunities for sustainable development*. Organisation for Economic Co-operation and Development. https://www.oecd.org/education/ai-in-education/

Priestley, M., Biesta, G., & Robinson, S. (2015). *Teacher agency: An ecological approach*. Bloomsbury Publishing.

Stronge, J. H. (2018). *Qualities of effective teachers* (3rd ed.). ASCD.

UNESCO. (2021). *AI and education: Guidance for policymakers*. United Nations Educational, Scientific and Cultural Organization. https://unesdoc.unesco.org/ark:/48223/pf0000376709

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – Where are the educators?

International Journal of Educational Technology in Higher Education, 16(1), 39. https://doi.org/10.1186/s41239-019-0171-0

Zheng, L., & Ren, L. (2022). The diminishing returns of digital investment in education: Evidence from smart classroom implementation. *Journal of Educational Administration and Policy Studies, 14*(1), 10–23. https://doi.org/10.5897/JEAPS2022.0740

Zhou, M., & Wang, Y. (2022). Exploring the role of institutional alignment in AI adoption in Chinese universities: Evidence from multiple case studies. *International Journal of Educational Management, 36*(7), 1178–1193.

Zimmerman, B. J. (2000). Attaining self-regulation: A social cognitive perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 13–39). Academic Press.