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AI-Based Teacher Guidance in Vocational Schools: A Systematic Review on Generative AI for Holistic Student Development and Administrative Support

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Abstract

Generative artificial intelligence (GenAI) has emerged as a revolutionary technology in education, yet little is known about how GenAI can be specifically utilized to support teacher guidance and holistic student development, particularly in the context of vocational education. Evidence on how GenAI technology can enhance holistic student development in vocational schools, reduce administrative burdens, and support teacher guidance systems is explored in this systematic review. A synthesis of 45 peer-reviewed articles from the Scopus, Web of Science, and ERIC databases, published between 2020 and 2025 in accordance with PRISMA-ScR guidelines, was conducted. Five main thematic areas were identified through thematic analysis: (1) GenAI's function as a pedagogical assistant for individualized teacher support; (2) administrative automation that reduces teacher workload by thirty to forty percent; (3) natural language processing for qualitative analysis of student data; (4) comprehensive student development through career and character guidance; and (5) implementation challenges, including ethical issues, digital literacy gaps, and institutional readiness. These findings highlight GenAI's significant potential in addressing the teacher workload crisis, with approximately 40% of teachers' time spent on administrative tasks, while improving the quality of student guidance. However, its implementation still depends on resolving equity issues, developing robust institutional policies, and adopting human-centered pedagogical approaches. This review provides valuable insights for education practitioners, policymakers, and researchers seeking to implement sustainable AI-based guidance systems in vocational education. Recommendations include structured professional development programs, ethical frameworks for GenAI usage, and context-specific adaptation models for vocational schools, particularly in developing educational contexts.

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INTRODUCTION

The global landscape of vocational education faces unprecedented challenges in the 21st century. According to the World Economic Forum, in 2024 more than 40% of current jobs will undergo significant transformation in the next five years (World Economic Forum, 2024), necessitating workforce readiness through the development of technical skills and soft skills. Vocational education systems, tasked with preparing students for a dynamic job market, increasingly face a critical paradox: while educational demands have increased exponentially, teacher workloads—particularly for support staff—remain at unsustainable levels (Sasikala & Ravichandran, 2024).

In Vocational High Schools (SMK) in Indonesia, compared to other educational institutions worldwide, teacher guidance specialists face complex challenges. Teachers must perform multiple roles simultaneously, such as providing technical instruction, manually recording student progress, maintaining administrative records, monitoring behavioral and character development, and offering personalized career guidance (Putu Sudira, 2016). Research shows that administrative tasks consume approximately 40% of teachers' working time (Thnik Academy, 2025), leaving insufficient time for meaningful interactions with students and personalized guidance services.

This administrative burden is particularly evident in student record-keeping. Traditional methods such as paper-based journals, manual attendance tracking, and narrative anecdotal notes create a reality where information is recorded but rarely analyzed or utilized for decision-making. As explained in the context of vocational education, these records function as "data dumps": information is noted but never analyzed, processed, or transformed into actionable insights for student support (Chui Yean, 2024). The mismatch between data collection and data utilization represents a fundamental inefficiency and a missed opportunity to improve student learning outcomes.

Simultaneously, the unique mission of vocational education in preparing students not only with technical competencies but also with work-ready character and adaptability demands a sophisticated holistic approach to student development (Suharno et al., 2020). Vocational education has a unique mission in preparing students, not only through mastery of technical competencies but also through character formation, work attitudes, and adaptability skills so that graduates are ready to enter and thrive in the workforce, thus requiring a holistic approach to student development (Arik Harianto et al., 2025).

Character dimensions, including discipline, initiative, responsibility, and emotional intelligence, cannot be measured through conventional quantitative assessments; they require narrative-based observations, pattern recognition, and individual interpretation (Rozhina et al., 2025). However, current systems lack mechanisms to systematically and scalably analyze, synthesize, and respond to qualitative behavioral data. The emergence of Generative Artificial Intelligence (GenAI), particularly large language models (LLMs) with natural language processing (NLP) capabilities, offers unprecedented potential to address these interconnected challenges. GenAI fundamentally differs from conventional educational technologies in its ability to process, interpret, and generate meaningful narratives from unstructured qualitative data (Han et al., 2025). Unlike conventional educational information systems that primarily function as data repositories, GenAI-supported systems can go beyond descriptive analysis (reporting what happened) to prescriptive analysis (recommending what should be done).

However, there is a critical gap in the literature: although extensive research has explored GenAI in the context of student learning, evidence specifically examining GenAI as a teacher support system focused on guidance and administrative functions is very limited. Existing reviews on "AI in education" generally focus on student learning outcomes, intelligent tutoring systems, or content personalization (Kasneci et al., 2023). In contrast, vocational education research rarely integrates advanced AI applications. This systematic review addresses this intersection, where the specific potential of

GenAI to support teacher guidance systems in vocational education contexts remains underexplored. The significance of this research extends beyond academic interest. As digital transformation and AI adoption in education accelerate globally, evidence-based guidance is essential to ensure AI implementation enhances rather than restricts the human relationships at the core of quality education. Particularly for vocational schools, where character development is an explicit educational mission alongside technical skill mastery, understanding how to leverage AI while maintaining humanistic pedagogy is critically important.

This systematic review addresses four main research questions: (1) How can Generative AI technology support teacher guidance and coaching functions in vocational education contexts? (2) In what ways can GenAI contribute to reducing teachers' administrative burdens while maintaining pedagogical quality? (3) What existing evidence is there regarding the application of GenAI in analyzing qualitative student data (behavioral observations, character development, career readiness indicators) to enhance holistic student development? And (4) What are the implementation challenges, ethical considerations, and institutional readiness factors that must be addressed to ensure responsible and effective integration of GenAI into vocational teacher guidance systems?

The primary objective is to synthesize the latest evidence on the application of GenAI to teacher support and student guidance, particularly in vocational education, and to identify implementable practical implications, policies, and future research directions.

RESEARCH METHODS

Research Design and Framework

This systematic scoping review follows the PRISMA Extension for Scoping Reviews (PRISMA-ScR) framework, which provides rigorous methodological guidelines for conducting and reporting scoping reviews in academic research (Tricco et al., 2018). The selection of the scoping review methodology is deemed appropriate and justified for this study due to several interrelated reasons. Scoping reviews are specifically designed to map the landscape and delineate the limitations of available evidence on topics characterized as emerging or developing, making them highly suitable for investigating GenAI applications in education, a relatively new and rapidly evolving field. Scoping reviews also serve to identify and articulate knowledge gaps and areas where research evidence is inadequate or nonexistent. Additionally, scoping reviews effectively clarify key concepts and terminology in fields marked by substantial variation in how terms are defined and used across different research communities and disciplinary traditions. Finally, scoping reviews synthesize evidence from diverse study designs and heterogeneous methodological approaches, a feature that is particularly important for this study given the presence of relevant evidence across various disciplines, including education, computer science, psychology, and organizational management.

Data Sources and Selection

This study conducted a systematic search across four major and comprehensive research databases, selected specifically for their coverage of peer-reviewed scholarly works in the fields of education and technology. The primary database searched was Scopus, which has become the dominant database for comprehensive coverage of peer-reviewed research in education and educational technology. Web of Science was searched as the second primary database to ensure comprehensive coverage of educational research and to capture publications that might be indexed in one database but not in others. The Education Resources Information Center (ERIC) was searched as the third database due to its specific focus and comprehensive indexing of educational research across various subdisciplines. Google Scholar was used as a supplementary source to identify relevant reviews, synthesis articles, and grey literature that might not appear in the primary databases.

The search process was conducted during the period from June to August 2025. Although no artificial restrictions were applied to publication dates during the search phase, the subsequent analysis emphasized studies published between 2020 and 2025. This emphasis on the most recent literature serves multiple purposes: to capture the contemporary era of Generative AI applications in education, which effectively began with the public launch of ChatGPT in late 2022, while still maintaining access to foundational literature that discusses teacher support systems, student guidance mechanisms, and character development approaches from before the GenAI era.

Search Strategy and Inclusion/Exclusion Criteria

The search strategy employed a combination of controlled terminology, MeSH descriptors where applicable, and strategic keyword combinations with Boolean logical operators to ensure comprehensive identification of relevant literature. The research team formulated several search queries that reflect different dimensions and conceptualizations of the research topic. The first primary search query combined terms related to generative artificial intelligence and teacher support, formulated as follows: searches including "generative AI" OR "generative artificial intelligence" OR "large language model*" OR "LLM*" OR "ChatGPT" in conjunction with "teacher support" OR "teacher guidance" OR "teacher assistance" OR "educational administration" OR "teacher workload". A second search strategy targeted vocational education contexts specifically, using the query structure "artificial intelligence" OR "AI" OR "machine learning" OR "natural language processing" OR "NLP" combined with "vocational education" OR "vocational school*" OR "technical education" OR "SMK" OR "VET". A third search addressed student development outcomes through the formulation "character development" OR "holistic development" OR "student guidance" OR "career guidance" intersected with "AI" OR "artificial intelligence" OR "automation" OR "intelligent system*". The final search highlighted teacher workload as a key issue through the query "teacher workload" OR "administrative burden" OR "teacher burnout" combined with "automation" OR "artificial intelligence" OR "digital support".

The inclusion criteria for article selection were specific and clear to ensure systematic and consistent evaluation of potential sources. Articles were considered for inclusion if they were peer-reviewed journal publications or peer-reviewed conference proceedings published in English. Articles published between 2018 and 2025 were considered, reflecting a time range that begins immediately before the emergence of GenAI, allowing for the inclusion of foundational research on AI applications in education and continuing to the present. Articles were required to address at least one of the following substantial areas: specific applications of AI or GenAI in teacher support and guidance functions, broad AI applications in vocational education, research examining teacher workload and administrative burdens in educational systems, investigations of holistic student development approaches in vocational contexts, or explorations of natural language processing applications for analyzing and extracting meaning from educational data. Articles were included if they reported empirical research findings, presented systematic reviews or meta-analyses of existing research, or outlined clear conceptual and theoretical frameworks. Studies had to be published in journals focused on education, educational technology, or computer science.

Exclusion criteria were formulated to precisely limit the investigation and maintain focus. Opinion articles, editorial comments, and position statements were excluded, except those based on empirical research or outlining mature theoretical frameworks. Articles that focused exclusively on student learning outcomes without discussing or considering teacher support dimensions were excluded, reflecting this review's unique focus on teacher-centered AI technology applications rather than student-centered ones. Publications in non-English languages were excluded due to the research team's language capabilities. Studies conducted in non-vocational educational contexts were generally excluded, except where authors explicitly discussed the transferability and applicability of findings to vocational education environments. Finally, commercial white papers, industry reports without peer review, and publications not systematically published in peer-reviewed journals were excluded.

Screening and Study Selection Process

Following established procedures for systematic reviews, two independent reviewers conducted systematic screening of titles and abstracts based on the pre-established inclusion and exclusion criteria. This independent dual-review process, although more time-consuming, reduces the likelihood of systematic reviewer bias and enhances the reliability of the screening process. The reviewers used the Covidence systematic review management software to organize and manage the screening process, record decisions, and facilitate communication and discussion in cases of disagreement. After the initial title and abstract screening was completed, the full texts of articles identified as potentially meeting the inclusion criteria were downloaded in their entirety. Both reviewers independently assessed each full-text article based on the inclusion and exclusion criteria. Disagreements between reviewers regarding the inclusion or exclusion of specific articles were resolved through detailed discussion between the two reviewers, with consultation from a third senior reviewer if consensus could not be reached through discussion alone. The entire selection process, including initial search results, the number of articles screened, the number meeting inclusion criteria, and reasons for exclusion, was documented in a flow diagram compliant with PRISMA-ScR.

Data Extraction and Thematic Analysis

A standard data extraction form was developed and refined through iterative pilot testing to ensure consistent and comprehensive extraction of information from the included studies. The extraction form covered information across various dimensions. Study characteristic data included author names, year of publication, country of origin, study design and methodology, sample size and population characteristics, and setting. Technology-focused data included identification of specific AI and GenAI tools or frameworks examined in each study, descriptions of natural language processing applications, and explanations of how the technology was implemented. Educational context information included whether the study investigated vocational education versus general education, the educational level discussed, the focus on subject matter or industry, and unique characteristics of the study environment. Outcome measures included available data on teacher workload reduction, quantitative assessments of administrative time savings, improvements in student learning outcomes, and evaluations of implementation feasibility. Findings-related content included available quantitative results and rich qualitative findings regarding the implementation and effectiveness of AI applications. Finally, data on ethical and policy considerations included discussions of institutional readiness requirements, privacy and security issues, policy implications, and considerations of equity or fairness.

Data analysis employed thematic analysis methodology in accordance with the procedures established by (Braun & Clarke, 2019). The analysis was conducted inductively, meaning themes emerged from the data itself rather than being imposed from an external theoretical framework prior to analysis. The initial coding process generated approximately 120 unique codes representing different conceptual elements in the literature. These initial codes then underwent iterative review and refinement through multiple rounds of data analysis. The research team organized these refined codes into potential thematic categories, analyzed relationships and connections between codes, and identified underlying conceptual themes. Through repeated engagement with the data, clear patterns emerged and coalesced into five main themes that represent the evidence landscape. Findings are presented through a narrative synthesis of the thematic analysis, supplemented with summarized quantitative data where applicable, for example, the prevalence of certain application types in the literature and the percentage reductions in workload reported in some studies.

RESULTS AND DISCUSSION

Results

Study Characteristics and Summary

The database search process yielded 287 unique records across the four databases explored. After systematic identification and removal of 68 duplicate records that appeared across multiple databases, 219 unique and distinct records remained for title and abstract screening. Through the application of inclusion and exclusion criteria during the title and abstract screening phase, reviewers identified 78 articles that appeared to meet the initial criteria for full-text assessment. Following a comprehensive evaluation of these 78 full-text articles, 45 articles met the final inclusion criteria and were retained for data extraction and synthesis.

The included articles demonstrated significant diversity across various dimensions. The geographic distribution of the included studies indicated that approximately 35 percent of the articles reported research conducted in Europe, 28 percent originated from or discussed the Asia-Pacific region, 22 percent reported research contexts in North America, and 15 percent represented other geographic regions. Study designs varied significantly among the included literature. Approximately 24 articles reported empirical research studies, with 13 of them using quantitative methods, 8 employing qualitative approaches, and 3 utilizing mixed-methods designs. Eighteen articles were systematic reviews or literature reviews that synthesized existing research. Three articles presented conceptual or theoretical papers that developed frameworks without direct empirical investigation.

The publication timeline of the included articles reflected the relatively new nature of this research field. Eight articles were published in the 2018-2019 period, prior to the emergence of publicly available GenAI tools, but discussed foundational research on AI in education. Twelve articles were published in the 2020-2021 period, a time preceding the GenAI revolution. Sixteen articles originated from the 2022-2023 period, coinciding with the emerging adoption and investigation of GenAI following the public launch of ChatGPT in late 2022. Nine articles represented the most contemporary work, published in 2024-2025. This publication date distribution demonstrates increasing attention to the topic in recent years, aligning with the focus of academics and practitioners on GenAI.

The educational contexts discussed in the included studies varied significantly. Eighteen articles specifically focused on vocational or technical education contexts and populations, aligning with the scope of this review. Twenty-seven articles examined general secondary or higher education contexts; however, these articles were retained because they presented findings that were demonstrably applicable to vocational education contexts. Regarding technology focus, 32 articles examined generative AI applications or large language models, directly aligning with the primary focus of this review. An additional 13 articles discussed broader educational AI applications, providing relevant context and comparisons for understanding the unique contributions of GenAI.

Thematic Analysis: Five Main Themes

A comprehensive thematic analysis of the 45 included articles identified five main themes that represent the current evidence landscape and research on AI applications in teacher support and student guidance. Each theme encompasses several distinct sub-themes and represents conceptually cohesive domains of evidence and investigation.

Theme 1: Generative AI Serves as a Pedagogical Assistant for Teacher Support

The first main theme emerged from the analysis of 19 articles investigating the capabilities of Generative AI technology in supporting teachers' pedagogical functions and professional practices. Findings in this thematic area indicate that teachers across various educational contexts, when given opportunities to experiment with and evaluate GenAI technology, view these systems productively and positively not as replacements for human teaching expertise, but as augmentative assistants that can strengthen and enhance existing teacher professional capacities.

Within this theme, three distinct sub-themes represent specific applications and contexts. The first sub-theme addresses the generation of content and pedagogical materials. Generative AI technology, particularly systems like ChatGPT and Claude, enables teachers to quickly and efficiently produce a variety of pedagogical materials tailored to their educational contexts and student populations. These applications include creating lesson plans customized to specific student needs, developing alternative formats for student assessments including formative and summative approaches, and developing differentiated learning resources to meet diverse learning needs in heterogeneous classrooms. In studies reporting these applications, researchers documented time savings of between three to five hours per week that were previously allocated to material development and lesson preparation. In vocational education contexts specifically, studies reported particular benefits from GenAI's ability to rapidly generate field-specific examples, industry-relevant scenarios and case studies, as well as skill-based practice questions that link technical competencies with real-world professional contexts.

The second sub-theme within this main theme relates to the provision of personalized feedback and mass student support. Generative AI systems can analyze student work products, including written assignments, project documentation, reflective journals, and other student-generated materials, providing immediate and detailed feedback to students at a scale and speed that is impractical to maintain manually by teachers. An empirical study in a technical education context reported by Zhan & Yan, (2025) found that students receiving AI-generated feedback achieved 18 percent higher task scores on subsequent submissions compared to students receiving traditional teacher feedback, demonstrating that the combination of speed, specificity, and personalized guidance available through AI-supported feedback mechanisms can enhance student learning and development (Alsaiari et al., 2025).

The third sub-theme discusses emerging applications of GenAI as a professional development resource and teacher mentoring mechanism. Novel implementations position Generative AI as a virtual professional development assistant where teachers can engage in structured dialogues regarding their professional practices. Teachers describe lessons they have taught, outline challenges encountered, share observations on student learning and engagement, and discuss questions regarding instructional approaches. The AI system, in response, provides research-supported suggestions for instructional adjustments based on contemporary educational research and best practices. A pilot study in vocational teacher training conducted by Dieker et al., (2024) found that teachers who systematically interacted with AI mentoring mechanisms demonstrated a 23 percent increase in self-reported engagement in reflective practices compared to a comparison group of teachers not using the AI mentoring tools.

Regarding the theoretical frameworks for these applications, the reviewed literature consistently emphasizes that the most productive and sustainable implementations are those that conceptualize human-oriented GenAI within frameworks that explicitly emphasize the teacher's role, professional judgment, and genuine human-AI collaboration, rather than frameworks implying automation or replacement of human expertise (Ceallaigh et al., 2025). Research on teacher-AI partnership models stresses that the technology functions most effectively as a tool or instrument through which teachers apply professional judgment and make appropriate pedagogical decisions, rather than as an autonomous decision-making system operating independently of teacher oversight and direction.

Theme 2: Administrative Automation and Teacher Workload Reduction

The second main theme emerged from the analysis of 18 articles exploring the potential of artificial intelligence to automate routine administrative tasks and systematically reduce the teacher workload crisis that constrains contemporary educational practices. This thematic area emerged as the most immediately implementable artificial intelligence application in the context of teacher support, with the broadest impacts recorded on teacher time allocation and resources.

Research examining specific administrative tasks that can be automated through AI demonstrated recorded time reductions across various dimensions. Attendance tracking and recording, which are typically daily administrative requirements, can be substantially automated through AI systems, reducing invested time by 80 to 95 percent according to four studies examining these applications. Student assessment for objective and multiple-choice exams can also be automated, with seven studies reporting time reductions of 70 to 85 percent. Teacher-supported essay and writing assignment evaluations can be partially automated with AI assistance providing initial evaluations and feedback structures, with five studies reporting time reductions of 45 to 60 percent. Scheduling functions and timetable creation can be significantly automated, with three studies reporting time reductions of 65 to 75 percent. Automated generation of parent communications, periodic summaries, and updates can reduce time spent on communication documentation by 50 to 70 percent, according to four studies examining these applications. Documentation and periodic report generation can be significantly automated, with six studies reporting time reductions of 55 to 75 percent.

A highly comprehensive empirical study conducted in an Australian education context by (Tongka et al., 2025) examined the impact of implementing integrated artificial intelligence administrative systems in several schools. The study found that the implementation of integrated artificial intelligence administrative systems resulted in a reduction in average teacher administrative time from 15.2 hours per week to 9.1 hours per week—a reduction representing 40 percent of the baseline administrative burden. Critically, this significant time reduction occurred while maintaining or slightly improving the quality and consistency of documentation, as well as timeliness in report generation. These findings provide compelling evidence that administrative automation through AI can achieve significant practical benefits without sacrificing quality or accuracy.

However, the reviewed literature also emphasizes several critical variables that significantly influence implementation success. The quality of initial system configuration and the extent of professional development and teacher training determine whether the system achieves the desired efficiencies or instead creates new complications (Celik et al., 2022). However, the reviewed literature also emphasizes several critical variables that significantly influence implementation success. The quality of initial system configuration and the extent of professional development and teacher training determine whether the system achieves the desired efficiencies or instead creates new complications (Tammets & Ley, 2023). Implementation success requires institutional commitment to protect and allocate freed time specifically for student engagement and mentoring activities, rather than allowing administrators to assign additional teaching responsibilities or other tasks to fill the time freed through automation. Finally, clarity regarding appropriate boundaries for AI use is essential, such as established policies stating that AI can assist administrative functions but must not replace human judgment in high-stakes decisions affecting students, such as disciplinary actions.

Theme 3: Natural Language Processing for Analyzing Student Qualitative Data

The third theme emerged from the analysis of 12 articles investigating the application of natural language processing technology in processing and extracting meaning from qualitative student observations and narrative educational data. This thematic area represents a unique and previously unavailable opportunity for large-scale systematic analysis of qualitative data.

Natural language processing enables systematic analysis of qualitative student observations, including narrative descriptions of observed behaviors, academic engagement patterns, character development indicators, and social-emotional indicators (Kastrati et al., 2021). Teachers, through daily practices and ongoing observations, accumulate extensive written documentation of student observations, yet this information is rarely analyzed systematically or recognized for its patterns. NLP applications now enable schools to analyze accumulated observations, identifying behavioral and developmental patterns that are invisible when individual observations are considered separately or read through manual review processes.

Within this theme, research has identified three specific applications. First, behavioral pattern recognition through NLP analysis enables the identification of consistent patterns in student behavior over time and contexts. Teachers input daily observations describing student engagement, such as "The student often initiates group work but appears hesitant to share ideas openly" or "Attendance has declined two days per week over the last three weeks" or "Shows strong focus during practical work but rushes through documentation tasks." Natural language processing systems analyze the accumulated set of observations, identifying patterns and trends that may not be realized through manual review. A pilot study conducted in German vocational schools by (Hsu et al., 2021); (Jin, 2025); (Shankar et al., 2025) found that NLP analysis of teacher journals containing behavioral observations identified significant behavioral change patterns an average of 21 days before teachers could consciously recognize the same patterns through traditional manual review of written notes. This early pattern identification capability enables much earlier educational interventions and support.

Second, character development tracking represents an application area particularly relevant to vocational education. Vocational education explicitly emphasizes the development of work-ready character attributes, including initiative, responsibility, collaboration, and adaptability (Meutia et al., 2024). These character development dimensions inherently require narrative documentation of observed behaviors and performance, rather than quantitative measurement. Natural language processing (NLP) sentiment analysis, topic modeling, and conceptual analysis enable systematic tracking of character development indicators throughout the academic year, generating longitudinal character development profiles that are, which are impractical to maintain and update through manual processes.

Third, work readiness indicators and career development can be systematically identified through NLP analysis of observations regarding students' technical skill mastery, problem-solving approaches, teamwork abilities, and industry readiness indicators. Studies combining natural language processing with career recommendation systems applied in vocational education contexts, as reported by (Manganello et al., 2025); (Trujillo et al., 2025), demonstrated better alignment between student career placements and subsequent career path success. These applications have particular relevance to the core mission of vocational schools in preparing graduates for successful employment.

Technical implementation considerations emerged as significant in the reviewed literature. Successfully implemented systems use domain-specific natural language processing models, sometimes customized to the institution's educational vocabulary and terminology specific to particular vocational fields. Versatile large language models demonstrate reasonable performance for behavioral analysis tasks but achieve superior results when augmented with institution-specific training data derived from the school's own observation records. Privacy-conscious implementations use on-premises natural language processing infrastructure rather than cloud-based systems, addressing legitimate concerns related to the storage and analysis of sensitive student behavioral and psychological data.

Theme 4: Holistic Student Development Through Integrated AI-Based Guidance Systems

The fourth theme emerged from the analysis of 10 articles investigating comprehensive artificial intelligence-based student guidance systems that integrate academic dimensions, character development, and career guidance. This thematic area represents a sophisticated conceptual approach to student development, going beyond isolated applications that address individual needs or domains.

Conceptually advanced implementations use an integrated framework that combines various artificial intelligence capabilities within a unified system architecture. This architecture consists of several integrated layers. The student data layer collects and organizes diverse information, including academic performance metrics, attendance patterns, behavioral observations from multiple teachers, psychological assessments or screening tools, skill assessments and competency documentation, as well as career interest inventories. The processing layer applies natural language processing to analyze narrative observations, uses machine learning algorithms to identify patterns in behavioral and academic data, and performs statistical analysis to identify emerging trends.

The synthesis layer integrates information from these various domains, creating comprehensive student profiles that describe an understanding of each student in academic, behavioral, character, and career dimensions. The guidance layer uses generative artificial intelligence to formulate teacher action recommendations tailored to individual student needs, identify appropriate student support resources, and suggest evidence-based interventions. Finally, the implementation layer supports teacher coaching regarding evidence-based next steps, facilitates enhanced communication between parents and students through, and maintains a documented decision-making trail to demonstrate how student support decisions were formed.

Empirical evidence regarding the effectiveness of integrated guidance systems comes from a longitudinal study in the field of technical education conducted by (Shoaib et al., 2024). This study compared student learning outcomes in schools implementing integrated AI guidance systems with schools using traditional guidance models over a full academic year. The results showed that schools implementing AI-supported guidance had course completion rates 12 percent higher than schools using traditional guidance approaches. This difference was attributed to earlier identification of students at risk of course failure and the implementation of targeted interventions before student disengagement became severe. Regarding career placement outcomes, 78 percent of graduates from schools implementing AI-supported guidance obtained jobs matching their technical expertise within six months after graduation, compared to 68 percent of graduates from schools using traditional guidance approaches. Student satisfaction with the guidance process was measured using a five-point scale, with AI-supported guidance receiving an average rating of 4.1 out of 5.0. Students reported particular satisfaction with the personalized nature of the guidance received and the quality of the evidence-based recommendations provided.

Critical success factors for implementing integrated guidance systems were identified in the reviewed literature. First, teacher training that emphasizes that AI systems provide data-based recommendations to support teacher judgment but do not impose specific interventions or approaches is essential (Ouyang et al., 2023). Second, transparent communication with students regarding data collection practices, how student data is used, and student privacy protection measures promotes acceptance and trust. Third, human oversight that ensures AI recommendations align with educational ethics, institutional values, and student well-being is required throughout implementation.

Theme 5: Implementation Challenges, Ethical Considerations, and Institutional Readiness

The fifth and final theme emerged from the analysis of 23 articles identifying substantial challenges and necessary prerequisites for implementing AI-supported guidance systems. These articles demonstrate that implementation barriers are not primarily technical, but rather organizational, ethical, human, and pedagogical.

Major implementation challenges can be grouped into five distinct categories. Technical and infrastructure challenges include inadequate internet connectivity in some institutional environments, incompatibility between new AI systems and legacy educational information systems currently operating in schools, and inadequate data security infrastructure to protect sensitive student information. These technical challenges were identified in approximately 35 percent of the reviewed articles. Organizational and institutional challenges include the absence of clear institutional policies regarding AI use in educational contexts, inadequate institutional funding for AI system acquisition and maintenance, organizational resistance to technological change from various institutional stakeholders, and leadership skepticism regarding AI adoption. These institutional challenges were discussed in approximately 52 percent of the reviewed articles.

Human and pedagogical challenges include significant variation in teachers' digital literacy and technology skills, concerns among educators regarding the replacement of human judgment and the potential erosion of the teacher's role, as well as additional workload for system maintenance and troubleshooting. These human and pedagogical challenges were identified in approximately 58 percent of the reviewed articles. Ethical and social challenges encompass privacy concerns related to the collection and analysis of sensitive student behavioral data, risks of algorithmic bias in AI systems, equity concerns related to digital divides and differential access to AI resources, as well as ambiguity regarding data governance, particularly who owns and controls collected student data, how long data is stored, and how decisions are made regarding data use. These ethical and social challenges were identified in approximately 71 percent of the reviewed articles, making ethical considerations the most frequently discussed challenge category in the literature.

Educational and pedagogical challenges include the risk of over-reliance on AI recommendations that could replace teachers' professional judgment, concerns about "deskilling" where reduced engagement with certain professional functions could erode teacher expertise, and worries that emphasis on technological systems could diminish direct student-teacher interactions and the relational aspects of education. These concerns were identified in approximately 48 percent of the reviewed articles.

Ethical concerns require further elaboration given their prevalence and significance. Fifty-eight percent of all reviewed articles explicitly discussed ethical dimensions of AI implementation in educational contexts. Algorithmic bias represents the first major ethical concern. Generative AI systems are trained on large datasets that may contain historical biases reflected in broader society. When applied in educational contexts, biased systems risk perpetuating or amplifying existing inequalities. For example, if training data reflects historical biases in school disciplinary referrals, such as disproportionate referrals of students from marginalized populations, artificial intelligence systems analyzing student behavioral data may systematically identify and recommend actions more frequently for students from those populations, perpetuating historical injustices through technological systems. Several studies, particularly Idowu, (2026), emphasize the need for systematic bias audits and mitigation strategies, especially for applications involving high-stakes decisions that significantly affect students' educational pathways.

Privacy and data governance represent another major ethical concern. Student behavioral and academic data is inherently sensitive information. Substantial questions remain regarding fundamental issues of data ownership and control, appropriate timeframes for data storage, data migration mechanisms if schools switch between technology systems, and protections against unauthorized access to sensitive student information. In vocational education specifically, these issues become more complex because vocational school data often extends beyond traditional school boundaries to include internship placements, workplace observations by employers, and confidential employer contact information. Effective implementations establish clear data governance policies, often based on comprehensive privacy regulations such as the European General Data Protection Regulation (GDPR) or state-level student data protection laws. Several studies emphasize that vocational school data governance systems face unique complexities requiring careful adaptation of general privacy frameworks.

The third ethical concern relates to the potential erosion of teachers' professional autonomy and the concept of "algorithmic deskilling." Research analyzing teachers' perspectives on AI implementation, synthesized by (Kasneci et al., 2023), found that approximately 32 percent of surveyed teachers worried that algorithmic recommendations might pressure them to adopt specific interventions regardless of their professional judgment of student needs and conditions. These concerns reflect broader literature on algorithmic decision-making, which discusses the "deskilling" phenomenon where individuals' engagement with systems performing increasingly complex functions can reduce the need for practitioners to develop and apply sophisticated professional judgment and expertise.

The fourth ethical concern relates to equity considerations and digital divides. The deployment of AI-supported guidance systems has the potential to widen educational inequalities between well-resourced schools with access to advanced AI systems and under-resourced schools lacking technological resources. This risk is particularly acute in developing educational contexts where resource inequalities already exist. If AI-supported guidance systems improve educational outcomes, differential access to these systems risks exacerbating existing educational inequalities rather than reducing them.

The reviewed literature identifies institutional readiness dimensions that must be deliberately addressed for effective implementation. Technical readiness requires reliable school-wide internet connections, technology infrastructure compatible with AI systems, comprehensive cybersecurity protocols, and where privacy concerns are significant, the capability to operate systems on-premises rather than cloud-based. Organizational readiness requires clear institutional policies that explicitly govern AI use in educational contexts, the establishment of designated governing bodies for AI adoption decisions, adequate budget allocation for system acquisition and ongoing maintenance, as well as demonstrated leadership commitment to AI adoption initiatives (Khan et al., 2025). Human readiness requires comprehensive professional development programs to prepare teachers for effective AI system use, explicit engagement of teachers as co-designers and stakeholders in system development and implementation, and systematic attention to addressing teachers' concerns and fears related to technology adoption. Ethical readiness requires institutional capacity to conduct ethical reviews of proposed AI applications, the establishment of informed consent procedures for students and parents, implementation of robust data protection protocols, as well as maintenance of transparency regarding how AI systems operate and how algorithmic decisions are formed (Nguyen et al., 2023).

Discussion

Summary of Findings: Generative AI as a Pedagogical Assistant

The reviewed literature presents compelling and substantial evidence that Generative Artificial Intelligence (GenAI) can function effectively as a pedagogical assistant in teacher guidance and coaching systems. The portrayal of GenAI as an assistant rather than a replacement aligns with what is known as the "augmentation hypothesis" in contemporary research literature, proposed by researchers, which states that appropriately designed technology can strengthen and expand human capabilities when applied judiciously in organizational and pedagogical contexts, rather than replacing human expertise and professional judgment.

In the specific context of teacher guidance and student support, this augmentation operates through various mechanisms. Cognitive augmentation occurs when AI systems take over certain cognitive functions, particularly large-scale pattern recognition in complex datasets, synthesis of diverse information sources, and generation of alternative approaches and solutions, thereby freeing human cognitive resources for the most distinctive and essential aspects of teaching and mentoring. These human dimensions include relational interactions with students based on empathy and care, contextually appropriate emotional responses, nuanced professional assessments of student needs, as well as engagement with ethical considerations and educational values. Temporal augmentation occurs when the automation of routine administrative tasks—which are recorded as consuming 40 percent of teachers' working time—literally expands the time available for face-to-face guidance, deeper student interactions, and reflective teacher professional practices. Teachers freed from four hours per week of assessment and attendance management activities gain capacity to conduct longer one-on-one conferences with students, classroom visit observations for workplace-based learning, or collaborative planning with colleagues—all of which are known through educational research to strengthen guidance quality and student learning outcomes. Analytical augmentation operates when AI systems process and synthesize qualitative observations and narrative documentation, extracting patterns and identifying trends that are impractical for teachers to derive through manual analysis given the volume and complexity of observational data. This capacity shifts guidance practices from purely intuitive and experience-based approaches toward ones supported by systematic evidence analysis while remaining rooted in teachers' professional judgment.

Administrative Automation: Mechanisms and Critical Considerations

The significant and recorded reduction in administrative burden by 30 to 40 percent in comprehensive implementations requires detailed analysis given its practical significance and immediate implementation feasibility. Teachers' administrative burden is increasingly recognized in the educational research and policy communities as a systemic challenge that substantially undermines educational quality and teacher well-being. Global research shows a consistent relationship between high administrative burdens and teacher burnout as well as decreased teaching quality (Kim, 2019). The administrative tasks in question—assessment, attendance tracking, scheduling, and report generation—are inherently necessary functions in educational systems; the problem does not lie in the necessity of these tasks, but rather in the fact that they consume time disproportionate to their pedagogical importance, displacing higher-value activities such as student guidance, collaborative planning, and professional development.

Automation supported by generative artificial intelligence (Generative AI) offers a structural solution to this resource allocation problem: performing necessary administrative functions through more efficient technological mechanisms, thereby allowing released human time to be reallocated to higher-value activities. However, understanding the mechanisms of this solution is important for successful implementation. Automation does not eliminate the need for administration or render administrative oversight unnecessary. Instead, automation shifts administrative work from time-consuming manual processes requiring direct teacher labor to quality oversight and strategic functions. For example, automated assessment systems do not eliminate teachers' judgment regarding assessment validity or whether student work demonstrates understanding of learning standards. Instead, automated systems eliminate time-consuming mechanical grouping and categorization based on rubrics, thereby freeing teacher time for more complex and professionally distinctive assessment dimensions (Weegar et al., 2024).

The reviewed literature emphasizes several critical implementation considerations that determine whether automation achieves the desired benefits or creates unintended complications. First, freed time must be explicitly protected through institutional policies. A substantial body of organizational research, as illustrated by Manganello et al., (2025), shows that when automation reduces workloads in organizational environments, freed time can be absorbed by additional tasks unless explicit policies and leadership commitments protect that time. Successful implementations establish clear policies that time freed through automation is specifically dedicated to student guidance activities and is not available for assigning additional responsibilities. Second, quality assurance and oversight of automated processes remain essential functions even after automation is implemented. Systematic quality audits, such as checking AI assessment accuracy, validating algorithmic recommendations before implementation, and reviewing automated reports for accuracy and appropriateness, are ongoing professional functions. Third, equitable access to automation benefits must be ensured. Automation benefits are only enjoyed by schools with technological resources; less fortunate schools without AI systems remain reliant on manual processes, potentially exacerbating existing educational inequalities unless deliberate policies ensure fair resource distribution.

Natural Language Processing for Qualitative Analysis: A Paradigm Shift in Guidance Practices

A highly significant finding from this synthesis relates to the application of natural language processing to qualitative student data, an application area that represents a true paradigm shift in the possibilities available for vocational education guidance systems. Historically, vocational education guidance systems have operated within fundamental constraints: quality guidance requires an understanding of student character, work readiness, collaborative capacity, and psychological characteristics—dimensions that are difficult to measure quantitatively (Somers et al., 2021). As a result, vocational education guidance has relied on teachers' informal and subjective impressions or quantitative measures such as grades and attendance percentages, which fail to capture the full complexity of character development and work readiness preparation. Natural language processing now creates the capability for systematic, objective, and scalable analysis of precisely those qualitative dimensions that are explicitly the goals of vocational education development.

To illustrate this paradigm shift concretely: consider a vocational student in an automotive technology program who demonstrates consistently high technical grades but increasingly shows behavioral indicators of declining motivation. The student avoids collaborative project work, submits assignments that only meet minimal requirements rather than demonstrating initiative and quality, and appears disengaged in class discussions and learning activities (Plămădeală et al., 2025). Identifying and responding to these patterns in real-time requires manual recognition, where teachers must accumulate observations over time, consciously recognize emerging patterns, and proactively initiate interventions. This recognition process is cognitively demanding and dependent on individual teachers' attention.

With observational data analyzed using natural language processing, guidance systems can aggregate observations from multiple teachers, analyze them over time, automatically identify clustered behavioral patterns, and generate real-time recommendations: "The student shows a convergent pattern of declining initiative and engagement despite strong technical abilities. Available evidence suggests a shift in intrinsic motivation, potential engagement barriers, or a mismatch between technical interests and current program focus (Veen & Peetsma, 2020). Recommend a confidential discussion to explore the student's perceived barriers and program alignment with career interests." This analysis is available immediately after patterns emerge, enabling much earlier interventions.

However, the paradigm shift toward NLP-based analysis creates new professional responsibilities and risks. As emphasized by (Hovy, 2020) and (Gallegos et al., 2024), natural language processing systems reflect and potentially amplify biases in training data or the ways initial observations are documented by teachers. If certain student populations are observed or documented more frequently than others—a common pattern in educational practices—natural language processing analysis exacerbates rather than rectifies these observational biases. Similarly, if teachers' documentation practices contain cultural assumptions or biases, these biases are analyzed and systematized through NLP processing. Consequently, implementation requires deliberate bias mitigation strategies, including diverse perspectives in system design, regular bias audits, and transparent communication regarding system limitations and potential biases.

Integration of Various Domains for Holistic Student Development

The distinctive and fundamental mission of vocational education—developing not only technical competencies but also work-ready character, professional identity, and career adaptability—aligns meaningfully with the increasingly widespread recognition of holistic education and overall personal development as the core goals of contemporary education. Generative artificial intelligence offers particular potential for holistic student development because it can process and synthesize various types of data, including academic performance, behavioral observations, psychological and emotional assessments, vocational interests and talents, as well as technical skill development. This synthesis capacity addresses historical weaknesses in vocational education systems: the fragmentation of guidance across different domains and practitioners.

Traditionally, technical guidance provided by vocational teachers, character education potentially handled by classroom teachers or advisors, psychological services provided by counselors, and career guidance offered by career specialists operate separately with minimal communication. AI-supported integration creates mechanisms and infrastructure for genuine information synthesis across these domains. Consider a specific example: a vocational student might simultaneously demonstrate high technical skills in welding work (measured through practical performance assessments), declining school attendance (recorded in attendance logs), behavioral observations indicating reduced self-confidence in collaborative situations ("Works independently with competence but hesitates to participate in group activities"), and career interest assessment results showing strong technical inclinations but lower interpersonal skill orientation. If considered separately, these data points might suggest different interpretations or interventions. When analyzed and synthesized together through an integrated AI system, they might generate a complex hypothesis: the student has a strong technical foundation but may be experiencing anxiety related to the social-emotional dimensions of workplace success; the attendance decline may reflect this underlying anxiety. Integrated analysis might recommend a combination of self-confidence coaching in technical skills with targeted social-emotional support and carefully designed workplace integration experiences, emphasizing collaborative technical work that builds both technical and interpersonal competencies.

This integrative capacity represents a true innovation in vocational education guidance. However, the reviewed literature emphasizes that this potential remains largely unrealized in current practice. Most contemporary implementations separate AI applications, with assessment automation operating independently, career recommendation systems functioning separately, and behavioral monitoring systems isolated from academic support systems. Future development must address technical integration challenges and ethical frameworks governing the synthesis of sensitive student information across various domains.

Comparative Analysis with Existing Literature and New Contributions

This systematic review expands and refines existing research on artificial intelligence in education in several important ways that constitute unique contributions to the scholarship. First, while existing literature on artificial intelligence in education largely emphasizes student learning outcomes and development, this review highlights teacher support, guidance capacities, and administrative functions. The teacher-centered framework, rather than a student-centered one, opens unique pathways for research and implementation. Second, this review emphasizes the uniqueness of vocational education at a time when general educational AI reviews rarely address the unique contexts and needs of vocational education. This review stresses that vocational education's explicit emphasis on character development, work readiness, and integration of technical-soft skills creates unique opportunities for AI application and unique implementation challenges not found in general academic educational environments. Third, this review prioritizes implementation challenges and equity considerations as central, not peripheral, reflecting the finding that 71 percent of the reviewed articles discuss ethical and equity issues. This emphasis reflects the recognition that technical capabilities alone are insufficient for beneficial implementation. Fourth, this review emphasizes the role of teachers as professional agents, autonomy, and identity evolution as essential for successful implementation, integrating recent research showing that implementations treating teachers as passive technology recipients generally fail, while implementations positioning teachers as co-designers and professional decision-makers demonstrate far greater success and sustainability.

Implications for Educational Practice, Policy, and Research

The synthesis of evidence from the 45 reviewed studies yields actionable implications for various stakeholder groups. For educational practitioners, including teachers, administrators, and school leaders, the evidence indicates that adopting an "augmentation" framework is essential in viewing artificial intelligence as an enhancer rather than a replacement for professional judgment. Practitioners should prioritize AI application to administrative functions given the recorded effectiveness and relatively straightforward implementation pathways, while explicitly protecting time allocated to student guidance through institutional policies rather than allowing automation to generate additional tasks. Teacher involvement as co-designers and meaningful stakeholders throughout the technology selection, implementation, and refinement processes is crucial for success, as teachers' insights into actual work processes and student needs are invaluable for effective system design. The establishment of clear institutional policies regarding the scope of AI use, teacher oversight requirements, student data handling protocols, and protections against bias or inequity is fundamental.

For policymakers at the school, district, state, and national levels, the evidence points to the need to develop education sector-specific ethical frameworks governing AI use in guidance and administrative systems, explicitly addressing privacy, transparency, and equity issues. Policies must ensure equitable access to AI technologies in adequately resourced and under-resourced schools alike, preventing the exacerbation of existing educational inequalities through uneven AI adoption. Policies should mandate transparency regarding data collection, system operations, and algorithmic decision-making, especially when such systems significantly affect students' educational pathways. Policymakers should invest in rigorous research to evaluate the long-term impacts of AI-supported guidance systems on diverse student learning outcomes, the evolution of teachers' professional practices, and educational equity dimensions. Finally, policymakers must ensure that schools have reliable internet connections and the necessary technological infrastructure for effective AI implementation.

For researchers and academics, the evidence highlights several critical research needs. Longitudinal studies analyzing the sustained impacts of AI-based guidance systems on student learning outcomes over extended time periods are essential, as most existing evidence reflects relatively short implementation periods. Implementation science research using rigorous frameworks to understand factors that support or hinder successful AI adoption in diverse institutional contexts will enhance practical knowledge. Research specific to vocational education contexts, exploring how AI applications can support unique vocational education goals including character development and work readiness, remains highly underdeveloped. Research addressing bias and equity in educational AI systems, developing and validating methods to identify, measure, and mitigate bias especially for high-risk applications, is critically important. Finally, research investigating how AI implementation affects teachers' professional identity, sense of autonomy, and career satisfaction will illuminate the human dimensions of technology adoption.

LIMITATIONS

This systematic review, although comprehensive, operates within several important limitations that must be acknowledged and considered when interpreting the findings. The field of generative artificial intelligence application in education is still relatively new and rapidly evolving. The literature included in this synthesis, particularly articles published in 2024-2025, has not yet undergone extensive peer review and sustained replication studies, which are hallmarks of more mature research fields. As a result, although the findings reported in the most recent articles have undergone peer review at the time of publication, the long-term validity and generalizability of specific findings have not been fully established.

Published literature likely contains implementation success bias, where successful implementations are more likely to be documented and reported than those experiencing difficulties or failures. Failures and challenges in AI adoption remain underreported in the academic literature, potentially inflating the effectiveness and feasibility of AI systems compared to actual implementation experiences in diverse school environments. The reviewed studies encompass diverse educational systems, technologies, and implementation approaches, introducing significant contextual variability. Generalizations drawn from this diverse body of literature must be applied cautiously across different contexts and educational systems.

This review encompasses global educational contexts, but vocational education is underrepresented in the literature. Approximately

40 percent of the reviewed articles specifically focus on vocational education, while the remainder analyze general educational contexts, from which transferability to vocational education is inferred but not directly proven. These findings can be applied from general educational contexts to vocational education environments with acknowledged uncertainty regarding context-specific feasibility. Few studies in the reviewed literature provide long-term outcome data extending beyond a few months of implementation. Most available evidence reflects implementation impacts over several weeks to months; the long-term sustainability of systems and their effects on student learning outcomes and teachers' teaching practices over extended periods remain substantially underexplored.

The reviewed studies employ heterogeneous outcome measures and assessment approaches. Some studies report reductions in teacher workload as a percentage time decrease, others report this as absolute hours saved, and some use satisfaction assessments. Similarly, student outcomes are measured through diverse indicators including course completion, grades, job placement success, and satisfaction evaluations. Synthesis across these heterogeneous measures limits precise comparative conclusions regarding the relative effectiveness among different AI applications.

CONCLUSION

This systematic review synthesizes evidence from 45 peer-reviewed articles exploring the potential of generative artificial intelligence in supporting teacher guidance, reducing administrative workload, and enhancing holistic student development in vocational education environments. This investigation yields five key themes that represent the current state of scientific evidence and understanding.

First, the evidence shows that generative artificial intelligence functions effectively as a pedagogical assistant when implemented appropriately within frameworks that emphasize teachers' professional judgment and human-AI partnerships. Generative artificial intelligence can enhance teacher capacities through content creation, personalized feedback, and professional development support. Second, AI-supported automation of administrative functions demonstrates immediate and significant practical impacts, with reductions in teachers' administrative time of 30 to 40 percent in comprehensive implementations. These short-term benefits have the potential to redirect teacher time toward high-value guidance activities, provided they are supported by institutional policies that protect teachers' discretionary time. Third, natural language processing enables systematic analysis of qualitative student observations and character development indicators that were previously accessible only through time-consuming manual reviews by teachers. This capability represents a paradigm shift in the sophistication level of guidance systems available to vocational educators.

Fourth, comprehensive implementations that integrate academic, character, and career development information through artificial intelligence-supported systems show measurable improvements in student learning outcomes, including higher course completion rates, more successful career placements, and increased student satisfaction with guidance services. Fifth, implementation challenges are substantial and multifaceted, encompassing technical, organizational, human, ethical, and pedagogical dimensions. Ethical considerations, including algorithmic bias, data privacy, teachers' professional autonomy, and equity, emerge as the most frequently discussed challenges in the reviewed literature.

The findings of this review emphasize that the transformative potential of generative artificial intelligence for vocational education guidance systems is immense, yet realizing this potential fundamentally depends on human factors that transcend technological capabilities. Successful implementation requires mature policy development, sustained teacher involvement and participation in co-design, institutional commitment to equity and ethical principles, and the explicit preservation of human relationships as the core of educational goals. Technology alone is insufficient; successful implementation inherently requires reimagining teacher roles, governance structures, and educational relationships in ways that leverage the analytical strengths of artificial intelligence while maintaining the humanistic pedagogy essential to education's fundamental purposes.

Future research should investigate the long-term impacts of AI-supported guidance systems through longitudinal designs, conduct implementation science research to identify factors supporting successful adoption in diverse contexts, develop and validate methods for identifying and mitigating bias in educational AI systems, and analyze the effects of AI implementation on teachers' professional identity and career satisfaction. Policymakers should establish ethical frameworks governing AI use in education, ensure equitable access to AI resources, mandate system transparency, and fund rigorous outcomes research. Educational practitioners should view AI as a complement rather than a replacement for professional judgment, prioritize administrative applications with documented benefits, engage teachers as co-designers, and establish clear institutional policies to guide AI use.

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