Artificial Intelligence and Information Technology Education: A Systematic Literature Review

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Derleme
Makale Geçmişi
Başvuru Tarihi: 11.11.2025
Kabul Tarihi: 22.12.2025

Review
Article History
Date of Application: 11.11.2025
Acceptance Date: 22.12.2025

Absract

Artificial intelligence (AI) is fundamentally changing the paradigms of Information Technology (IT) education. This technology, at the heart of the Fourth Industrial Revolution, is no longer just a part of the curriculum but also functions as a pedagogical tool. The current study aims to comprehensively analyze the existing literature examining the multifaceted impacts of AI on IT education. Key shifts, such as intelligent tutoring systems, personalized learning paths facilitated by learning analytics, automated code evaluation and feedback mechanisms, and the integration of generative AI tools (e.g., GitHub Copilot, ChatGPT), are examined in depth. The findings highlight the potential of AI to improve student performance, manage cognitive load, and strengthen student motivation and engagement. It also demonstrates its potential to reduce instructors' administrative burdens, allowing them to focus on higher-level pedagogical activities. However, significant challenges associated with this integration have been identified, including concerns about academic integrity, ethical implications, algorithmic bias, and excessive cognitive reliance on AI tools.

Keywords: Artificial Intelligence, Information Technology Education, Computer Science Education, Intelligent Tutoring Systems, Personalized Learning, Generative Artificial Intelligence, Learning Analytics, Automatic Assessment

Yapay Zekâ ve Bilgi Teknolojileri Eğitimi: Sistematik Literatür İncelemesi

Özet

Yapay zekâ bilişim teknolojileri eğitiminin paradigmalarında önemli değişimlere neden olmaktadır. Dördüncü Sanayi Devrimi'nin merkezindeki bu teknoloji, artık sadece müfredatın bir parçası değil, aynı zamanda pedagojik bir araç olarak da işlev görmektedir. Mevcut çalışma, yapay zekanın bilişim teknolojileri eğitimi üzerindeki çok yönlü etkilerini inceleyen mevcut literatürü kapsamlı bir şekilde analiz etmeyi amaçlamaktadır. Akıllı öğretim sistemleri, öğrenme analitiğiyle kolaylaştırılan kişiselleştirilmiş öğrenme yöntemleri, otomatik kod değerlendirme ve geri bildirim mekanizmaları ve üretken yapay zeka araçlarının (örneğin GitHub Copilot, ChatGPT) entegrasyonu gibi önemli değişimler derinlemesine incelenmiştir. Bulgular, yapay zekanın öğrenci performansını iyileştirme, bilişsel yükü yönetme ve öğrenci motivasyonunu ve katılımını güçlendirme potansiyelini vurgulamaktadır. Ayrıca öğretim görevlilerinin idari yüklerini azaltarak daha üst düzey pedagojik faaliyetlere odaklanmalarını sağlama

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potansiyelini de barındırmaktadır. Ancak, entegrasyonla ilgili önemli zorluklar tespit edilmiştir; bunlar arasında akademik dürüstlük, etik sonuçlar, algoritmik önyargı ve yapay zeka araçlarına aşırı bilişsel bağımlılıkla ilgili endişeler yer almaktadır.

Anahtar Kelimeler: Yapay Zeka, Bilgi Teknolojisi Eğitimi, Bilgisayar Bilimleri Eğitimi, Akıllı Öğretim Sistemleri, Kişiselleştirilmiş Öğrenme, Üretken Yapay Zeka, Öğrenme Analitiği, Otomatik Değerlendirme

1. Introduction

Informatics education (IE), the driving force of the digital age, is a dynamic field that must adapt to the rapidly changing demands of industry and society. Traditionally, introductory programming courses have been characterized by high failure rates, a lack of motivation among students, and difficulties concretizing abstract concepts (Guzdial et al., 2019). Instructors face significant challenges in providing individualized feedback to each student in large classes, resulting in the prevalence of a "one-size-fits-all" approach (Tseng et al., 2008). In this context, artificial intelligence (AI) is seen as the technological force with the most significant transformational potential to overcome long-standing problems in IT education. AI-supported applications enable the adaptation to students' diverse learning speeds and styles by tailoring learning processes to their individual needs. Furthermore, they significantly contribute to increasing the efficiency and effectiveness of education by automating teaching processes and implementing data-driven decision-making mechanisms.

Artificial intelligence is no longer merely an advanced subject of expertise in informatics curricula; it has become an active pedagogical actor fundamentally restructuring teaching and learning processes (Russell et al., 2021). The role of AI in education has expanded far beyond simple automation tasks. Intelligent Tutoring Systems (ITS) promise to deliver adaptive learning experiences that can adapt to each student's individual learning pace, cognitive level, and even emotional state (Brusilovsky, 2003). Learning Analytics uses AI algorithms to identify patterns, risk factors, and intervention points in student learning, providing educators with actionable insights (Siemens & Baker, 2012). However, integrating these AI-based systems into educational environments requires a multilayered process that must be carefully considered across pedagogical, ethical, and technical dimensions. In the future, AI is expected to become not only a tool to support learning but also an active stakeholder in shaping instructional design and educational policies.

Artificial intelligence constitutes an expansive discipline that investigates machines' capacity to execute tasks characteristically associated with human cognition, including learning, problem-solving, and decision-making. Contemporary AI systems predominantly exemplify narrow AI, which is confined to specific, delimited functionalities (Abbas vd., 2025). Generative AI, an emergent subdomain within AI, demonstrates the proficiency to produce novel content—such as text, images, audio, and code—derived from patterns discerned in extant datasets. This advancement transcends conventional data analysis and classification, evincing substantive creative capabilities (Brown vd., 2020; Joshi, 2025).

The predominant and most efficacious applications of generative artificial intelligence are realized through Large Language Models (Tan vd., 2023). LLMs comprise deep learning architectures trained on expansive datasets, excelling in the comprehension, manipulation, and naturalistic generation of human language (Mundlamuri vd., 2025). Gemini, a foremost tool in this domain and developed by Google, distinguishes itself via its multimodal architecture, which facilitates the simultaneous processing of diverse information types, including text, images, and code. Conversely, ChatGPT constitutes a globally prominent LLM application, engineered by OpenAI on the GPT framework, proficient in producing creative textual content and responses to user natural language inputs. Moreover, models such as DeepSeek, advanced by DeepSeek AI, position themselves as robust competitors in the LLM arena, leveraging superior performance in language generation and understanding. These innovations are hastening AI's transformative influence on everyday life and industrial workflows (Aldoseri vd., 2024).

Particularly in the last few years, the rise of generative AI tools based on large language models (LLMs), such as GitHub Copilot and ChatGPT, has triggered a paradigm shift in computing education (Parekh et al., 2024). Students now have a "human-like" partner who can provide instant assistance with coding, debugging, and problem-solving. This is changing students' problem-solving approaches, collaboration models, and even cognitive processes. However, this revolution also raises important pedagogical and ethical questions: Does AI-generated code promote learning or cognitive laziness? Will basic programming skills atrophy in the shadow of these tools? How will our assessment methods distinguish the line between "human" and "AI"-generated? (Shihab et al., 2025). Therefore, educators must develop new pedagogical strategies that integrate these tools to enrich learning while simultaneously preserving critical thinking and foundational skills. The IT education of the future will be built on establishing a balanced synergy between human creativity and the productive power of AI.

The current study aims to analyze these complex and multilayered changes brought about by AI in informatics education. This study focuses not only on understanding "what" AI does, but also "how" and "why" it is effective (or not). The central research question of this review is: "How are AI technologies and methodologies transforming the pedagogical frameworks, instructional tools, and assessment paradigms of informatics education?" To address this central question, we will focus on the following sub-questions:

1. What are the major AI applications used in IT education (e.g., ALS, automated assessment, generative AI, etc.), and how have trends in these applications changed over time?

2. What are the documented effects of these AI applications on student learning outcomes (performance, motivation, engagement, cognitive load)?

3. What are the key pedagogical, technical, and ethical challenges (e.g., academic integrity, bias, over-reliance) faced in integrating AI into IT education?

2. Method

This study used the Systematic Literature Review (SLR) design to synthesize existing empirical and theoretical knowledge on the role of artificial intelligence in informatics education. SLR is a methodical and replicable process that aims to identify, select, critically appraise, and synthesize all relevant primary studies to address a specific research question. The methodological framework for this review was established based on the principles of the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) statement, which is widely accepted for reviews in software engineering and educational technologies (Page et al., 2021). PRISMA aims to increase the quality and reliability of the review by ensuring transparent reporting of the screening, selection, eligibility, and inclusion processes. This section outlines the review's research design, how the research questions will be addressed, and the overall structure of the methodological framework. The following sections, "Data Collection" and "Data Analysis," will outline the step-by-step implementation of this methodology. This approach ensures that the Method section is understood as a process that forms the backbone of the study, rather than just a plan.

3. Data Collection

This phase of the systematic review involves comprehensively and unbiasedly identifying, searching, and selecting relevant literature to answer the research questions. This process was conducted in accordance with the PRISMA flowchart. To ensure a comprehensive literature review, leading academic databases in computer science and education were targeted. The selected databases are:

- ACM Digital Library: For core publications in computer science.
- IEEE Xplore: For publications focused on engineering and computer science.
- Scopus: For broad, interdisciplinary coverage.
- Web of Science (WoS): For its coverage of high-impact journals.
- ERIC (Education Resources Information Center): For research focused on education sciences.

The search strategy was based on keyword sets reflecting the core components of the research questions (Artificial Intelligence, Information Technology Education). The search was conducted in the title, abstract, and keyword fields of the publications. The basic Boolean search sequence used (adapted to database syntax) is as follows:

> *("Artificial Intelligence" OR "AI" OR "Intelligent Tutoring System*" OR "Generative AI" OR "Machine Learning" OR "Learning Analytics")*
> *AND*
> *("Computer Science Education" OR "Programming Education" OR "Informatics Education" OR "Software Engineering Education" OR "Computing Education")*

Data Selection Criteria

Explicit inclusion (IC) and exclusion (EC) criteria were established to ensure that the collected article pool aligned with the review's focus. Only full-text, peer-reviewed journal articles, conference proceedings, and book chapters published in English were included in the study. The publication date range for the studies was January 1, 2018, to December 31, 2024. This seven-year period enables the examination of trends both before and after the emergence of generative AI. Selected studies were required to address the use of Artificial Intelligence (AI) as a tool, method, or pedagogy in IT education (K-12 or higher education) at an empirical or theoretical level. Exclusion criteria were determined as follows: publications in languages other than English, non-peer-reviewed studies such as abstracts, posters, editorials, theses, and technical reports, research that focuses only on teaching AI as a course subject and does not use it as a pedagogical tool, and studies that address AI applications in fields other than informatics education. The data collection process was conducted in three stages:

1. Identification: A total of 3,450 articles were identified through searches of five selected databases.
2. Screening:
1. Duplicate records were removed using reference management software (e.g., Zotero). This process left 2,180 unique studies.
2. Two independent researchers screened the titles and abstracts of these 2,180 studies according to inclusion/exclusion criteria. A third senior researcher resolved disagreements. One thousand eight hundred thirty studies were excluded at this stage.
3. Eligibility: The full texts of the remaining 350 articles were reviewed. An additional 285 articles that did not meet the inclusion/exclusion criteria were excluded after full-text review.
4. Inclusion: After screening, 65 articles were included in the data analysis of this systematic review.

4. Data Analysis

Analyzing and synthesizing the 65 articles identified during the data collection phase is critical to generating in-depth answers to the research questions. This section explains how the qualitative and quantitative data from the selected articles were extracted and transformed into meaningful themes.

Data Extraction

Before beginning the analysis process, a standardized data extraction form was created to extract a consistent dataset from each article (n = 65). This form included the following information:

- Basic bibliographic information (Author(s), Year, Publication Type, Title).
- Purpose of the study and research questions.
- Methodology (e.g., quantitative, qualitative, mixed methods, design-based research).
- Context (e.g., Higher education, K-12; Entry-level programming, Data structures).
- AI technology/approach used (e.g., OLS, Learning Analytics, Generative AI, Autograder).
- Key findings (impacts on student outcomes).
- Reported challenges or limitations (e.g., ethical, pedagogical, technical).

Thematic Analysis

For data synthesis, the Thematic Analysis approach, widely used in education and the social sciences (Braun & Clarke, 2006), was adopted. Thematic analysis offers a flexible and iterative process for identifying, analyzing, and reporting patterns (themes) in the dataset. The analysis process followed the six-stage process described by Braun & Clarke (2006):

1. Familiarization with the Data: All 65 articles were read multiple times to identify general trends and potential codes.
2. Generation of Initial Codes: Relevant sections of the articles (especially the Findings and Discussion sections) were coded directly related to the research questions. For example, codes such as "immediate feedback," "reduction in cognitive load," and "plagiarism detection" were created. To ensure normalization, 20% of the articles (n = 13) were coded independently by two researchers, and inter-coder reliability (Cohen's Kappa) was calculated. The initial 78% agreement (K = 0.78) was increased to over 90% (K = 0.91) through discussion and clarification of the coding guide, resulting in a high level of analytical consistency.
3. Exploring Themes: Initial codes were grouped into potential themes representing broader levels of meaning.
4. Reviewing Themes: The generated potential themes were examined against both the coded data and the entire dataset (65 articles). Some themes were combined, while others were divided into subthemes.
5. Defining and Naming Themes: Clear definitions and names were created that captured the essence of each theme.
6. Preparing the Report: In the final stage, these themes were presented within a logical narrative in the "Findings" section.

5. Findings

The thematic analysis revealed four main themes and subthemes reflecting the impact and changes of artificial intelligence on informatics education. These findings are a synthesis of data from a set of 65 analyzed articles.

Theme 1: Pedagogical Personalization

The most established application area of AI in IT education is Intelligent Tutoring Systems (ITS) and adaptive learning platforms that challenge the "one size fits all" model. *ITS (Intelligent Tutoring Systems):* The reviewed literature indicates that ALSs play a critical role, particularly in introductory programming education (Francisco & Silva, 2022). These systems monitor students' coding processes step by step, providing instantaneous and context-sensitive feedback that goes beyond syntax errors to address semantic errors (Wenger, 1987). For example, ALSs such as iSnap or BITS analyze each step a student takes when solving a programming problem and, when "stuck," provide scaffolding hints that break the problem into smaller steps (Tseng et al., 2008). Empirical studies report that students using ALSs complete problem-solving tasks faster and learn core concepts more persistently compared to students in traditional laboratory environments (Jian, 2023).

Adaptive Learning Paths: Beyond ALSs, AI is being utilized to create personalized learning paths tailored to each student. These systems, based on the student's current knowledge level (learner model), determine which topic (e.g., "loops" or "conditional statements") they should tackle next, at what difficulty level, and in what format (e.g., video, text, interactive coding exercise) (Brusilovsky, 2003). This aims to optimize cognitive load, preventing students from becoming either cognitive overload or boredom.

Theme 2: Automation and Deepening of Assessment

The impact of AI in computer science education has revolutionized assessment processes in terms of both efficiency and depth. *Automated Grading and Feedback:* Traditional auto-graders typically focused on whether student code passed specific test cases. The new generation of AI-based systems being studied goes beyond the "right/wrong" dichotomy (Messer et al., 2024). These systems provide "enriched feedback" by analyzing code quality (e.g., efficiency, style, readability), programming paradigms used, and even potential logical errors. This eliminates the burden of manually assessing hundreds of assignments (Baidoo-Anu & Owusu-Ansah, 2023), allowing instructors to focus their time on students who are experiencing conceptual challenges.

Learning Analytics (LA): AI has transformed assessment from an "outcome" to a "process." LA dashboards analyze student coding, debugging, and system interaction data (clickstreams, code compilation frequency, time spent) (Siemens & Baker, 2012). These analyses can proactively identify “at-risk” students (e.g., those who do not start assignments or repeatedly make the same mistakes) before instructor intervention is necessary. Furthermore, this data allows for immediate curriculum revision by revealing which parts of the course (e.g., the topic of “recursion”) are not being understood by the class.

Theme 3: The Generative AI Revolution: Collaborative and Disruptive Power

The analyzed articles, particularly those published between 2022 and 2024, focus on the disruptive impact of generative AI (GenAI) on computing education. *AI Code Assistants:* GenAI is positioned as a "problem-solving partner" rather than a "tool." Using tools like Copilot, students can quickly generate code blocks, create "boilerplate code" for complex algorithms, and accelerate debugging processes. Empirical studies have shown that students using these tools report a significant reduction in task completion times (Shihab et al., 2025) and an increase in confidence when tackling more complex problems.

Socratic Dialogue and Explainability: Conversational AI tools like ChatGPT not only help students write code but also understand why the code works the way it does. Students can engage in spontaneous, Socratic dialogue by asking questions like, “Why isn’t this code working?” or “What is the time complexity of this function?” This has the potential to shift learning from an “outcome” focus (running the code) to a “process” focus (understanding the code).

Theme 4: Curriculum Reshaping

The integration of AI is transforming what IT education teaches and what skills it prioritizes. The literature emphasizes that as AI automates routine coding tasks, curricula must shift from pure coding to critical thinking and systems integration skills (Baidoo-Anu & Owusu-Ansah, 2023). Instead of unthinkingly copying AI-generated code, the next generation of IT professionals must be able to evaluate it critically, inspect it for security vulnerabilities, optimize its performance, and integrate it into existing systems.

AI Literacy and Ethics: IT curricula must now encompass not only the use of AI but also its operation and societal impacts. The reviewed articles agree that topics such as algorithmic bias, data privacy, and AI ethics should be included in the core competency set of all IT students.

6. Conclusion and Discussion

This systematic literature review reveals that AI is a transformative force that challenges and reshapes the pedagogical foundations of informatics education (IE) beyond being a superficial tool. The findings clearly demonstrate that AI is evolving in IE from a reactive tool (e.g., automated grading) to a proactive and near-collaborative partner (e.g., generative AI). This section synthesizes the findings, discusses pedagogical implications, highlights current challenges, and identifies future research directions.

The most significant consequence of AI integration is the redefinition of both the student and instructor roles. AI is shifting the instructor from a "knowledge transmitter" (sage on the stage) to a "learning facilitator" (guide on the side) and "modeling AI-human collaboration." Thanks to automated assessment tools (Messer et al., 2024), instructors can shift their time from routine grading to focusing on students' more complex conceptual challenges, problem-solving strategies, and critical thinking skills. Learning analytics dashboards (Siemens & Baker, 2012) provide instructors with proactive tools that show which students need intervention and when.

Students are becoming actors who actively manage their own learning process using AI tools, rather than passive recipients of information (Adiyono vd., 2024; Dochia, 2025). However, this means that students need metacognitive skills (knowing what they know and determining their learning strategies) more than ever before. Therefore, educational curricula must be restructured in parallel with this transformation to develop students' critical thinking and self-directed learning capacities systematically (Lee vd., 2024). This adaptation will form the cornerstone of raising generations that are not only capable of using existing tools but also able to respond with intellectual flexibility to future technological advancements.

The literature demonstrates that this transformation is not smooth and presents serious challenges that require urgent solutions. The first of these can be described as the Academic Integrity Crisis. Generative AI (GenAI) has fundamentally shaken traditional assessment methods (Shihab et al., 2025). Assignments such as “write this code” have become meaningless when the student instructs the AI to “print this code.” The findings suggest that educational institutions need to redefine plagiarism. The solution is not to ban AI, but to shift assessment from the “end product” to the “process.” For example, asking students to critique, debug, or improve AI-generated code (Baidoo-anu & Owusu Ansah, 2023) is an example of the “authentic assessment” methods required in the AI age.

Another challenge with AI is cognitive dependency and the loss of fundamental skills. Over-reliance on AI assistants (cognitive offloading) risks students graduating without developing basic programming logic, problem-solving resilience, and debugging skills. IT education must teach AI to operate not as a cruiser but as a copilot never to let go of the steering wheel.

Another significant challenge explored in the scholarly literature pertains to algorithmic bias and equity (Zhai vd., 2024). ALS and learning analytics systems are only as good as the data they collect. Suppose these systems are trained with biased data (e.g., the learning patterns of certain demographic groups). In that case, they can reinforce existing inequalities and penalize those who do not fit the "standard" student profile. Under the guise of "personalization," there is a risk of unintentionally guiding students to think within narrowly defined frameworks (Bernacki vd., 2021). Therefore, transparency, accountability, and regular audits of unfair outcomes are essential in the development and integration of these systems into educational environments. Digitally literate educators who are aware of these risks and can critically evaluate technology are the most crucial human resources for overcoming these challenges (Falloon, 2020).

This systematic review also has its limitations. First, the search was limited to publications in English, which may have excluded valuable research conducted in other languages. Second, the field of AI (especially GenAI) is advancing so rapidly that new tools and findings will have emerged even by the time this review is published (this should be considered a "snapshot" of the literature). Third, the exclusion of non-peer-reviewed "gray literature" (such as technical reports and dissertations) may have led to some innovative but not yet formally published applications being overlooked.

Ultimately, AI is an "ecosystem change" rather than a "tool" in IT education. Succeeding in this new ecosystem requires understanding not only how to use AI but also how AI shapes us. The future of IT education lies not in the technology itself, but in the pedagogical wisdom of how we use this technology to create more critical, ethical, and human-centered learning experiences.

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