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Reimagining Economics Education Through Artificial Intelligence: Opportunities, Challenges, and Human-Centered Innovation

Madina Allahverdiyeva

Abstract. *The growing use of Artificial Intelligence (AI) is increasingly influencing the development of contemporary education. The application of AI technologies in teaching and learning offers new opportunities to improve the quality of education, promote greater student engagement, and provide more individualized learning experiences. In economics education, where analytical reasoning, data interpretation, and problem-solving abilities are essential, AI can provide innovative methods to support educators and facilitate students' learning processes. This paper explores the role of Artificial Intelligence in transforming economics education by examining its potential applications, emerging opportunities, and associated challenges. The study discusses how AI-based tools can contribute to adaptive learning, intelligent tutoring, automated feedback, economic data analysis, and interactive learning environments. At the same time, the paper highlights important concerns related to academic integrity, ethical use of technology, data privacy, digital inequality, and the changing role of educators. The paper argues that the successful integration of AI into economics education requires a human-centered approach where technology functions as a complementary instrument rather than a substitute for educators. By combining technological innovation with effective pedagogical strategies, AI can contribute to the development of more flexible, inclusive, and future-oriented economics education systems.*

Keywords: *artificial intelligence, economics education, educational technology, digital transformation, personalized learning, human-centered innovation, AI ethics*

Introduction

The rapid development of digital technologies has significantly transformed the structure, objectives, and practices of contemporary education. Among these technologies, Artificial Intelligence (AI) has emerged as a particularly influential tool with the potential to reshape traditional approaches to teaching and learning. The increasing availability of AI-based systems has created new opportunities for personalized instruction, automated feedback, data-driven learning, and more flexible educational environments. In higher education, AI applications are increasingly being explored as instruments for supporting both educators and students and for improving the efficiency and quality of educational processes (Zawacki-Richter et al., 2019; Bond et al., 2024; Castillo-Martínez et al., 2024).

Nakhchivan State University, PhD in Economics, Nakhchivan, Azerbaijan
E-mail: medineallahverdiyeva@ndu.edu
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Economics education is particularly relevant to the integration of AI because the discipline requires students to develop analytical thinking, data interpretation, quantitative reasoning, forecasting, and problem-solving skills. Economics students increasingly need to work with large datasets, interpret economic indicators, evaluate alternative scenarios, and make evidence-based decisions. In this context, AI-based technologies can provide opportunities for students to engage with economic data, explore complex relationships between variables, and apply theoretical concepts to practical situations. Intelligent tutoring systems, generative AI tools, adaptive learning platforms, and interactive simulations can therefore complement conventional approaches to economics education (Holmes & Tuomi, 2022; Kasneci et al., 2023).

Previous research on AI in higher education has emphasized its potential to personalize learning, improve student support, facilitate feedback, and assist educators with routine academic tasks. At the same time, the literature identifies significant challenges related to academic integrity, ethical responsibility, data privacy, technological dependence, and unequal access to digital resources. (Kasneci et al., 2023; Miao & Holmes, 2023; Bond et al., 2024). These challenges suggest that the educational value of AI cannot be determined solely by its technological capabilities. Rather, its effectiveness depends on the pedagogical context in which it is implemented and on the ability of institutions and educators to use AI responsibly.

Despite the growing body of research on AI in higher education, further attention is needed to the specific implications of AI for economics education. Economics has distinctive characteristics because of its strong reliance on quantitative analysis, economic modeling, forecasting, data interpretation, and evidence-based decision-making. Consequently, the opportunities provided by AI in economics education may extend beyond general personalization and automated support to include new forms of analytical and simulation-based learning. At the same time, the increasing use of AI raises questions about how students can develop independent analytical judgment while using technologies capable of generating information, analyses, and solutions. (Kasneci et al., 2023; Miao & Holmes, 2023; Bond et al., 2024).

This issue creates an important pedagogical challenge. AI should not simply be introduced as a technological replacement for existing educational practices. Instead, its integration should be guided by a human-centered approach that preserves the essential role of educators in developing students' critical thinking, creativity, ethical awareness, and independent judgment. In this perspective, AI functions as a supportive instrument that can expand educational opportunities while human expertise remains central to interpretation, guidance, evaluation, and meaningful interaction. (Holmes & Tuomi, 2022; Miao & Holmes, 2023). Against this background, this study aims to examine the opportunities and challenges arising from the integration of Artificial Intelligence into economics education and to explore the implications of a human-centered approach to AI-supported teaching and learning. The study focuses on three interconnected dimensions: the educational applications of AI, the potential benefits and risks of its integration, and the changing role of educators in AI-supported economics education.

The study addresses the following research questions:
1. What are the main opportunities for applying Artificial Intelligence in economics education?
2. What pedagogical, ethical, and technological challenges are associated with the integration of AI into economics education?
3. How can a human-centered approach contribute to the effective and responsible use of AI in economics education?

By addressing these questions, the study contributes to the discussion of AI in education by focusing specifically on economics education and by emphasizing the need to balance technological innovation with pedagogical principles and human expertise. Economics students increasingly need to work with large datasets, interpret economic indicators, evaluate alternative scenarios, and make evidence-based decisions (Aliyeva et al., 2026).

Methods

Research Design

This study employs a qualitative thematic review of the existing literature to critically examine the opportunities, challenges, and broader implications of Artificial Intelligence (AI) in economics education. This methodological approach is appropriate because the study seeks to synthesize and interpret insights from existing academic and institutional literature rather than collect and statistically analyze primary data. The thematic approach facilitates the identification of recurring patterns, emerging perspectives, and key areas of scholarly discussion concerning the application of AI in economics education, including its potential benefits, associated risks and challenges, and the evolving role of educators in AI-supported learning environments.

Literature Selection

The literature examined in this study consists of peer-reviewed academic publications, literature and systematic reviews, and relevant reports published by recognized international organizations. The selected sources address AI in education and higher education, with particular attention to its relevance to economics education. Sources were considered relevant when they addressed one or more of the following areas: personalized learning, intelligent tutoring systems, generative AI, automated feedback, data-driven learning, simulation-based education, academic integrity, AI ethics, data privacy, digital inequality, and the changing role of educators. Priority was given to recent publications reflecting the rapid development of AI and generative AI in educational contexts. Earlier influential studies were also included when they provided important conceptual or theoretical foundations for understanding AI applications in education. The selection of sources was guided primarily by their relevance to the research questions and their contribution to the study objectives.

Data Analysis

The selected literature was analyzed using thematic analysis. The analysis involved three main stages. First, the selected sources were reviewed to identify their main arguments, findings, and areas of focus. Second, recurring concepts and issues were identified and grouped into related categories. Third, these categories were organized into broader themes corresponding to the research questions of the study. The thematic analysis identified four interconnected areas. The first focused on the opportunities offered by AI within economics education, particularly personalized learning and intelligent tutoring systems. The second examined AI-supported analytical and practical learning, including data-driven learning approaches and simulation-based activities. The third explored the pedagogical, ethical, and technological challenges associated with integrating AI into economics education, with particular attention to academic integrity, data privacy, digital inequality, and the reliability of AI-generated information. The fourth considered the evolving role of educators and emphasized the importance of maintaining a human-centered approach to AI-supported economics education.

Methodological Scope and Limitations

This study is based exclusively on secondary sources and does not involve primary data collection from students, educators, or educational institutions. Therefore, the findings represent a thematic synthesis and interpretation of the existing literature rather than empirical evidence of the effectiveness of specific AI tools in economics education. The qualitative nature of the review also means that the interpretation of the literature involves a degree of researcher judgment. Nevertheless, organizing the reviewed literature according to clearly defined thematic areas and research questions provides a structured basis for identifying major opportunities, challenges, and implications of AI integration into economics education. The limitations of the literature-based approach are considered when interpreting the findings and formulating directions for future empirical research.

Statement on the Use of Artificial Intelligence

Artificial Intelligence tools were used during the preparation of this manuscript for language editing, grammatical improvement, structural organization, and refinement of academic expression. The author independently reviewed and verified the AI-assisted content and remains fully responsible for the accuracy, originality, interpretation, and final version of the manuscript. All AI-assisted content was critically evaluated and revised by the author to ensure its academic integrity and alignment with the objectives of the study.

Results

The thematic analysis of the selected literature identified four major areas concerning the integration of Artificial Intelligence into economics education: personalized and adaptive learning, AI-supported analytical and practical learning, pedagogical and ethical challenges, and the changing role of educators. These themes correspond to the research questions of the study and demonstrate that AI creates both new educational opportunities and significant implementation challenges. (Zawacki-Richter et al., 2019; Bond et al., 2024).

Personalized and Adaptive Learning

The reviewed literature indicates that one of the most significant opportunities associated with AI in education is the development of personalized and adaptive learning environments. AI-based systems can analyze students' learning progress, identify areas of difficulty, and provide individualized learning materials and feedback. Such systems may allow students to receive additional explanations or practice activities according to their learning needs and progress. For economics education, personalized learning is particularly relevant because students may differ considerably in their levels of mathematical, statistical, and analytical preparation. AI-supported systems can provide differentiated learning activities and assist students in working with economic concepts at different levels of complexity. The literature therefore suggests that AI can contribute to a more flexible learning environment in which students receive support according to their individual learning requirements (Crompton & Burke, 2023; Holmes & Tuomi, 2022). AI-based systems can support personalized learning by adapting educational content, learning activities, and feedback according to individual learning requirements (Crompton & Burke, 2023; Holmes & Tuomi, 2022; Teymurova, 2026).

AI-Supported Analytical and Practical Learning

A second major finding concerns the use of AI to strengthen analytical and practical learning. Economics education requires students to interpret quantitative information, analyze economic indicators, understand relationships between variables, and apply theoretical concepts to practical situations. AI-based technologies can support these activities by assisting learners with data analysis, pattern recognition, forecasting exercises, and scenario-based learning (Holmes & Tuomi, 2022). The reviewed literature also indicates that interactive simulations and AI-supported learning environments can help students connect theoretical knowledge with practical applications. Economic scenarios can be explored through digital environments in which students examine alternative conditions and observe potential outcomes. Such approaches may strengthen students' ability to interpret economic information and apply theoretical knowledge to practical problems (Kasneci et al., 2023).

Generative AI tools can additionally provide explanations, examples, and immediate responses to students' questions. However, the literature emphasizes that AI-generated information should be critically evaluated because such systems may produce inaccurate, incomplete, or misleading information (Kasneci et al., 2023). Consequently, AI-supported analytical learning requires students to develop skills in verification, interpretation, and critical evaluation.

Pedagogical, Ethical, and Technological Challenges
The thematic analysis identified several challenges that may limit the effective integration of AI into economics education. Academic integrity represents one of the most frequently discussed concerns, particularly following the rapid development of generative AI systems. Students may use AI-generated content in assignments without adequately demonstrating their own analytical abilities, creating challenges for traditional assessment practices (Kasneci et al., 2023; McDonald et al., 2024). Another important challenge concerns data privacy and security. AI-supported educational systems may require the collection and processing of information about students' learning activities and performance. This creates a need for transparency, informed use of data, and appropriate institutional safeguards (Miao & Holmes, 2023; Bond et al., 2024).

The literature also identifies unequal access to digital technologies and differences in digital competence as important barriers to effective AI adoption. Students and educational institutions may have different levels of access to reliable digital infrastructure, AI tools, and the knowledge required to use them effectively. Therefore, the implementation of AI may potentially reinforce existing educational inequalities if access and digital literacy are not addressed (Williamson & Eynon, 2020; Castillo-Martínez et al., 2024).

Changing Role of Educators and Human-Centered Integration
The fourth major finding concerns the changing role of educators. The literature does not support the view that AI should simply replace teachers. Instead, AI is increasingly described as a tool that can complement educators by supporting routine activities, providing learning assistance, and facilitating feedback (Zawacki-Richter et al., 2019; Bond et al., 2024; Tuomi et al., 2022). At the same time, educators remain essential for developing students' critical thinking, independent judgment, ethical awareness, and ability to interpret information. Human-centered approaches to AI in education emphasize the importance of maintaining human agency, meaningful interaction, transparency, and educator involvement in AI-supported learning environments (Alfredo et al., 2024; Bond et al., 2024). For economics education, this finding is particularly important because economic learning involves not only technical analysis but also interpretation, judgment, and evaluation of economic and policy-related consequences. AI can support the processing of information and exploration of scenarios, while educators continue to provide intellectual guidance and contextual interpretation.

Summary of the Results
Overall, the results indicate that AI integration into economics education can be organized around two complementary dimensions. The first is the educational potential of AI, including personalized learning, analytical support, interactive learning, and automated feedback. The second is the conditions required for responsible implementation, including academic integrity, ethical use, data protection, equitable access, digital competence, and continued human involvement. These findings provide the basis for the subsequent discussion of how AI can be integrated into economics education while maintaining a balance between technological innovation and human-centered pedagogy.

Discussion

The findings of this study indicate that Artificial Intelligence has considerable potential to transform economics education, particularly through personalized learning, intelligent tutoring, automated feedback, data-driven learning, and interactive learning environments. However, the findings also demonstrate that the educational value of AI depends on the conditions under which it is implemented. This supports the broader literature on AI in higher education, which emphasizes that technological capabilities alone do not guarantee improved educational outcomes (Zawacki-Richter et al., 2019; Bond et al., 2024; Castillo-Martínez et al., 2024).

The first major implication concerns personalized and adaptive learning. AI-based systems can provide learners with individualized support based on their learning progress and identified knowledge gaps. For economics education, this opportunity is particularly relevant because students may have different levels of mathematical, statistical, and analytical preparation. AI-supported learning environments may therefore provide additional explanations, examples, and practice opportunities according to individual needs. At the same time, personalization should not result in excessive automation of the learning process. Students still need opportunities to formulate questions, evaluate evidence, and develop independent economic reasoning (Crompton & Burke, 2023; Holmes & Tuomi, 2022).

The findings also highlight the importance of AI for data-driven and practice-oriented economics education. Economics increasingly depends on the analysis and interpretation of large amounts of quantitative information. AI can support students in identifying patterns, examining economic scenarios, and interpreting data. This can strengthen the connection between theoretical concepts and practical economic problems. However, the use of AI-generated analysis also creates a need for stronger verification and critical evaluation skills. Students should not treat AI-generated explanations or interpretations as inherently accurate. Instead, AI-supported analysis should be accompanied by source verification, comparison of alternative explanations, and critical examination of assumptions (Kasneci et al., 2023; Holmes & Tuomi, 2022).

The findings concerning academic integrity are consistent with the wider literature on generative AI in education. The increasing accessibility of AI-generated text and solutions challenges traditional approaches to assessment and raises questions about whether submitted work accurately reflects students' own knowledge and abilities (Kasneci et al., 2023; McDonald et al., 2024). For economics education, this issue is particularly important because assignments frequently require analytical reasoning, interpretation of economic evidence, and problem-solving. Consequently, assessment practices may need to place greater emphasis on students' reasoning processes, application of concepts, oral explanation, and reflection on how conclusions were reached rather than relying exclusively on final written outputs.

Another important implication concerns data privacy, transparency, and responsible use of AI. The collection and processing of student data can support personalization and learning analytics, but it can also create risks related to privacy, security, and user autonomy. Research on human-centered AI in education emphasizes the importance of balancing automation with human control, involving educational stakeholders in system design, and ensuring safety, reliability, and trustworthiness (Alfredo et al., 2024; Bond et al., 2024). Similarly, international guidance on generative AI in education emphasizes human agency, responsible use, and appropriate safeguards (Miao & Holmes, 2023; UNESCO, 2024).

The findings further suggest that digital inequality should be considered an important part of AI adoption strategies. Although AI can potentially expand access to educational support, unequal access to reliable internet connections, appropriate devices, digital skills, and AI-enabled educational services may produce new forms of inequality. Therefore, institutions should consider infrastructure and digital literacy alongside the introduction of AI-based educational technologies. AI integration should be accompanied by measures that ensure students have meaningful and equitable opportunities to use these technologies (Williamson & Eynon, 2020; Bond et al., 2024).

The changing role of educators is another central issue identified by this study. AI can reduce some routine tasks and provide students with additional learning support, but it does not eliminate the need for educators. Instead, the teacher's role may increasingly involve facilitating critical thinking, evaluating AI-generated information, designing meaningful learning activities, providing ethical guidance, and supporting students' intellectual development. Recent research on AI in education similarly emphasizes the importance of maintaining human agency and meaningful involvement of educators and students in AI-supported educational systems (Alfredo et al., 2024; Tuomi et al., 2022).

For economics education specifically, this human-centered perspective is particularly significant. Economics involves not only technical analysis but also interpretation, judgment, policy evaluation, and consideration of social and ethical consequences. AI can assist students in processing information and exploring alternative scenarios, but the interpretation of economic evidence and the evaluation of policy implications require human judgment. Therefore, AI should be positioned as a cognitive and educational support tool rather than as an autonomous substitute for the educator or the learner (Holmes & Tuomi, 2022).

The findings also have important implications for institutional policy and teacher development. Universities should provide educators with opportunities to develop AI literacy and pedagogical competencies that enable them to integrate AI into their courses in a responsible and effective manner. Institutional guidelines should clearly address appropriate AI use, academic integrity, data privacy, transparency, and assessment practices. At the same time, students should develop the ability to use AI tools responsibly while also critically questioning, verifying, and evaluating the accuracy and reliability of AI-generated information (Miao & Holmes, 2023; UNESCO, 2024).

Overall, the discussion suggests that the central issue is not whether AI should be introduced into economics education, but how it should be integrated. A sustainable approach requires alignment between technological capabilities, pedagogical objectives, ethical principles, and human expertise. The human-centered model proposed in this study therefore places educators and learners at the center of AI-supported educational innovation while using AI to expand opportunities for personalization, analytical learning, and practical application.

Conclusion

Artificial Intelligence is increasingly influencing the development of contemporary education and has significant potential to transform economics education. This study examined the main opportunities and challenges associated with the integration of AI into economics education and explored the importance of a human-centered approach to its implementation.

The findings indicate that AI can support personalized learning, intelligent tutoring, automated feedback, data-driven learning, and simulation-based educational activities. These applications can help students engage more effectively with economic concepts, quantitative information, and practical problem-solving tasks. AI can also support educators by reducing certain routine activities and creating additional opportunities for individualized student support.

At the same time, the integration of AI presents important challenges. Academic integrity, ethical responsibility, data privacy, unequal access to digital technologies, and the reliability of AI-generated information require careful consideration. The findings therefore suggest that technological adoption alone cannot ensure meaningful improvements in economics education. Effective implementation requires appropriate pedagogical strategies, institutional support, digital competencies, and clear ethical principles.

The study further emphasizes that educators should remain central to AI-supported economics education. AI should be used as a complementary educational instrument rather than as a substitute for human expertise. Educators play an essential role in developing students' critical thinking, independent judgment, ethical awareness, and ability to evaluate information. A human-centered approach can therefore combine the analytical capabilities of AI with the pedagogical and interpersonal capabilities of educators.

From a practical perspective, higher education institutions should invest in AI literacy, professional development for educators, responsible-use guidelines, and equitable access to digital technologies. Assessment practices should also be adapted to encourage independent reasoning, critical evaluation, and responsible use of AI-generated information.

Finally, this study is based on a thematic analysis of existing literature and therefore does not provide primary empirical evidence concerning the effectiveness of specific AI tools in economics education. Future research should examine AI-supported economics education through empirical studies involving students and educators and should investigate the effects of specific AI applications on learning outcomes, analytical skills, and student engagement.

Overall, the future of economics education should not be determined by whether Artificial Intelligence replaces traditional teaching, but by how effectively it can be integrated into educational practices while preserving human judgment, critical thinking, ethical responsibility, and meaningful interaction. A balanced human-centered approach can enable AI to serve as a strategic instrument for developing more flexible, inclusive, and future-oriented economics education.

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Mathematical Modeling and Analysis of Pid-Based Flight Control Systems for Unmanned Aerial Vehicles

Rashad Nematzade[1*], Mukhtar Azizullayev[2], and Gunel Rzayeva[3]

Abstract. *Unmanned aerial vehicles (UAVs) are increasingly used in civilian, industrial, and special-purpose applications due to their mobility, flexibility, and autonomous operating capabilities. One of the main technical challenges in UAV systems is maintaining stable flight performance under changing operating conditions and external disturbances. Flight stability directly affects navigation accuracy, maneuverability, and overall system reliability. Therefore, automatic flight control systems based on proportional-integral-derivative (PID) controllers remain widely applied in modern UAV platforms. This study presents the mathematical modeling and simulation-based analysis of PID-based flight control systems for UAV stabilization. The proposed approach focuses on roll, pitch, and yaw attitude control using a classical PID controller structure. The UAV dynamic model, PID control law, and main performance indicators, including overshoot, settling time, rise time, and steady-state error, are analyzed. Simulation results show that properly selected PID parameters significantly improve the dynamic response of the UAV attitude-control system. Compared with low-gain and medium-gain configurations, the optimized PID controller provides faster stabilization, lower steady-state error, and improved response smoothness. The study also discusses the advantages, limitations, and tuning challenges of PID controllers and indicates the future potential of adaptive and AI-based control methods for UAV stabilization.*

Keywords: *UAV, PID controller, flight control, stabilization, mathematical modeling, control systems*

Introduction

Unmanned aerial vehicles (UAVs) have become one of the most rapidly developing technological platforms in modern engineering. Their application areas include aerial monitoring, mapping, agriculture, logistics, search and rescue operations, environmental observation, and special-purpose missions. The increasing use of UAVs has created a strong need for reliable flight control systems capable of ensuring stable, accurate, and safe operation under different flight conditions.

One of the main technical challenges in UAV operation is flight stabilization. During flight, a UAV is continuously affected by external disturbances such as wind, vibration, payload variation, maneuvering forces, and sensor measurement errors. These factors may cause deviations in roll, pitch, and yaw angles, which directly influence the stability and controllability of the aircraft. Therefore, the development of effective automatic control algorithms is an important requirement for improving UAV flight performance (Mahony et al., 2012; Bouabdallah et al., 2004).

[1]Gazi University, PhD student, Ankara, Türkiye
[2]Azerbaijan Technical University, PhD student, Baku, Azerbaijan
[3]MAKA Research Institute of Aerospace Informatics, Baku, Azerbaijan
[*]Corresponding author. E-mail: resadneymetzade@gmail.com
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Among different control methods, the proportional-integral-derivative (PID) controller remains one of the most widely used approaches in UAV flight control systems due to its simple structure, practical implementation, and real-time error compensation capability (Li et al., 2006). In UAV systems, PID controllers are commonly used to regulate attitude angles, altitude, angular velocity, and trajectory tracking parameters (Bouabdallah et al., 2004; Mahony et al., 2012). Correct tuning of the proportional, integral, and derivative coefficients allows the system to achieve faster response, lower overshoot, and improved steady-state accuracy (Li et al., 2006).

Previous studies have shown that UAV control and communication reliability are closely related to the quality of onboard control architecture, flight-controller design, telemetry stability, and signal-processing mechanisms. Research works on UAV telemetry, control channels, signal quality, antenna parameters, and electronic interference have emphasized the importance of reliable system architecture for stable UAV operation (Aghayev et al., 2025; Azizullayev, 2025; Rzayeva et al., 2025a, 2025b; Azizullayev, 2026; Rustamov et al., 2025). In addition, studies related to national flight-card design and UAV telemetry systems show that flight-control hardware and software integration plays an essential role in ensuring autonomous and stable UAV performance (Nematzade & Rzayeva, 2024).

However, despite the wide use of PID controllers in UAV systems, the influence of PID parameters on dynamic response characteristics still requires detailed mathematical analysis. In particular, overshoot, settling time, rise time, and steady-state error are important indicators for evaluating the effectiveness of a UAV stabilization system. Improperly selected PID coefficients may lead to oscillations, slow response, or unstable flight behavior.

The main purpose of this study is to present a mathematical model and simulation-based analysis of PID-based flight control systems for UAV stabilization. The study focuses on the control of roll, pitch, and yaw motion using a classical PID controller. The influence of PID parameters on flight stability and dynamic response is analyzed through mathematical equations and response characteristics. The proposed approach provides a general and open scientific framework for evaluating UAV flight stabilization without depending on any restricted or confidential system data.

Recent studies have also investigated the influence of telemetry reliability, signal protection mechanisms, and communication stability on UAV control efficiency under different operating conditions (Rustamov et al., 2025; Azizullayev, 2026). Reliability improvement of radio-electronic subsystems is also considered an important factor in UAV operational stability (Nematzade et al., 2026).

Methods

This section presents the mathematical model of the UAV flight-control system, the structure of the PID controller, the governing control equations, and the simulation environment used for evaluating the stabilization performance of the UAV.

UAV dynamic model. In this study, the unmanned aerial vehicle is modeled as a rigid-body dynamic system with rotational motion around three principal axes: roll, pitch, and yaw. These rotational movements determine the flight attitude and stability of the UAV during operation. Future development may also include intelligent image-processing methods based on artificial neural networks for automatic recognition and classification of objects in the monitored environment (Nematzade et al., 2026). Distance measurement and sensing methods can also play an important role in the detection and localization of mines, particularly in systems designed to reduce direct human exposure to hazardous areas (Rzayeva et al., 2025b).

In addition, frequency-hopping-based communication approaches can improve the robustness of control and telemetry links in radio-electronic warfare and interference-prone environments (Azizullayev et al., 2026). External disturbances such as aerodynamic forces, environmental effects, and maneuvering conditions may influence these angular motions and reduce flight stability.

The rotational dynamics of the UAV can be mathematically expressed as follows:

$$J_\phi \ddot{\phi}(t) = \tau_\phi(t) \qquad (1)$$
$$J_\theta \ddot{\theta}(t) = \tau_\theta(t) \qquad (2)$$
$$J_\psi \ddot{\psi}(t) = \tau_\psi(t) \qquad (3)$$

where J_ϕ, J_θ, and J_ψ represent the moments of inertia around the roll, pitch, and yaw axes, respectively. The variables $\phi(t)$, $\theta(t)$, and $\psi(t)$ denote the angular positions, while $\tau_\phi(t)$, $\tau_\theta(t)$, and $\tau_\psi(t)$ denote the control torques generated by the propulsion and stabilization system.

For simplified dynamic analysis, the transfer function of the UAV rotational channel can be represented by the following second-order model:

$$G(s) = \frac{1}{Js^2} \qquad (4)$$

This transfer function describes the relationship between the applied control torque and the angular response of the UAV.

PID controller structure. The PID controller is used to minimize the difference between the desired reference angle and the measured output angle of the UAV. The control error signal is defined as:

$$e(t) = r(t) - y(t) \qquad (5)$$

where $r(t)$ is the reference input signal, $y(t)$ is the measured system output, and $e(t)$ is the control error. The mathematical expression of the PID controller is given by:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt} \qquad (6)$$

where $u(t)$ represents the controller output signal, K_p is the proportional gain coefficient, K_i is the integral gain coefficient, and K_d is the derivative gain coefficient.

The proportional term provides an immediate response to the error signal, the integral term reduces the accumulated steady-state error, and the derivative term improves damping characteristics and suppresses oscillations (Li et al., 2006). The combined operation of these three components enables effective stabilization of UAV attitude parameters, especially in roll, pitch, and yaw control channels (Bouabdallah et al., 2004; Mahony et al., 2012).

UAV stabilization equations. The PID-based roll stabilization equation is expressed as:

$$u_\phi(t) = K_{p\phi} e_\phi(t) + K_{i\phi} \int_0^t e_\phi(\tau) d\tau + K_{d\phi} \frac{de_\phi(t)}{dt} \qquad (7)$$

Similarly, the pitch stabilization equation is written as:

$$u_\theta(t) = K_{p\theta} e_\theta(t) + K_{i\theta} \int_0^t e_\theta(\tau) d\tau + K_{d\theta} \frac{de_\theta(t)}{dt} \quad (8)$$

The yaw stabilization equation can be represented as:

$$u_\psi(t) = K_{p\psi} e_\psi(t) + K_{i\psi} \int_0^t e_\psi(\tau) d\tau + K_{d\psi} \frac{de_\psi(t)}{dt} \quad (9)$$

The corresponding control error equations are given below:

$$e_\phi(t) = \phi_{ref}(t) - \phi(t) \quad (10)$$

$$e_\theta(t) = \theta_{ref}(t) - \theta(t) \quad (11)$$

$$e_\psi(t) = \psi_{ref}(t) - \psi(t) \quad (12)$$

where $\phi_{ref}(t)$, $\theta_{ref}(t)$, and $\psi_{ref}(t)$are the desired reference attitude angles for roll, pitch, and yaw motions.

Simulation environment. A simulation environment was developed to evaluate the performance of the proposed PID-based UAV stabilization system. The mathematical model was implemented using a second-order dynamic system, and different PID coefficient combinations were analyzed to investigate their influence on the system response characteristics.

The simulation parameters used in this study are presented in Table 1.

Table 1

Main simulation parameters

Parameter	Description	Value
J	Moment of inertia	0.025 kg·m²
ϕ_{ref}	Reference roll angle	10°
θ_{ref}	Reference pitch angle	10°
ψ_{ref}	Reference yaw angle	15°
Simulation time	Total simulation duration	10 s
Sampling time	Time interval	0.01 s
K_p	Proportional gain	1.2-3.0
K_i	Integral gain	0.05-0.4
K_d	Derivative gain	0.2-0.8

The performance of the UAV control system was evaluated using overshoot percentage and steady-state error criteria. The overshoot value is calculated as:

$$M_p = \frac{y_{max} - y_{ss}}{y_{ss}} \times 100\% \quad (13)$$

The steady-state error is defined as:

$$e_{ss} = | r - y_{ss} | \quad (14)$$

where $y_{max}$is the maximum output response, $y_{ss}$is the steady-state output value, and $r$is the reference input signal.

The simulation results obtained from these equations were used to analyze the influence of PID parameters on UAV flight stability, dynamic response, and control accuracy.

Results

This section presents the simulation results obtained for the PID-based UAV flight-control system. The analysis focuses on the dynamic response of the UAV attitude-control model, including response speed, overshoot, settling time, steady-state error, and stability comparison between different PID gain configurations.

Step response analysis. The step response of the UAV attitude-control system was analyzed using three different PID configurations: low-gain PID, medium-gain PID, and optimized PID. The aim was to determine how the variation of PID coefficients affects the stabilization process of the UAV.

Table 2

PID gain configurations used in simulation

Controller type	K_p	K_i	K_d
Low-gain PID	1.2	0.05	0.20
Medium-gain PID	2.0	0.20	0.45
Optimized PID	2.8	0.35	0.70

The simulation showed that the low-gain PID controller produced a slow response and required more time to reach the reference angle. The medium-gain PID controller improved the response speed, but a small overshoot was observed. The optimized PID controller provided the best balance between fast response, low overshoot, and minimum steady-state error.

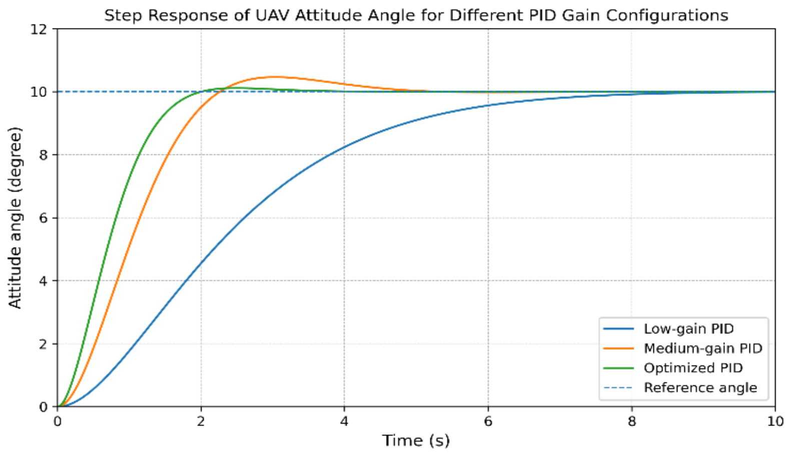

Figure 1

Step response of UAV attitude angle for different PID gain configurations

Figure 1 illustrates the step response of the UAV attitude angle under different PID gain configurations. The low-gain PID controller shows a slower response and reaches the reference value later. The medium-gain PID controller improves response speed but produces a small overshoot. In comparison, the optimized PID controller reaches the reference attitude angle more rapidly and maintains a stable response with minimal overshoot. These results confirm that appropriate PID parameter tuning significantly improves UAV attitude stabilization performance.

Dynamic response indicators. The main dynamic response indicators obtained from the simulation are presented in Table 3. These indicators are commonly used to evaluate the performance of flight-control and stabilization systems.

Table 3
Dynamic response characteristics of PID-based UAV control system

Controller type	Rise time, s	Settling time, s	Overshoot, %	Steady-state error, degree
Low-gain PID	2.40	5.80	1.5	0.42
Medium-gain PID	1.55	3.40	4.8	0.18
Optimized PID	0.95	2.10	2.2	0.05

According to the obtained results, the optimized PID controller reduced the settling time from 5.80 s to 2.10 s compared with the low-gain PID configuration. This indicates that the optimized controller achieved faster stabilization after the reference command was applied. At the same time, the steady-state error decreased from 0.42° to 0.05°, which demonstrates improved angular accuracy.

Overshoot and settling time comparison. Overshoot and settling time are important parameters in UAV flight stabilization. High overshoot may cause unwanted oscillations and reduce flight safety, while long settling time may delay the stabilization process after maneuvering or external disturbance.

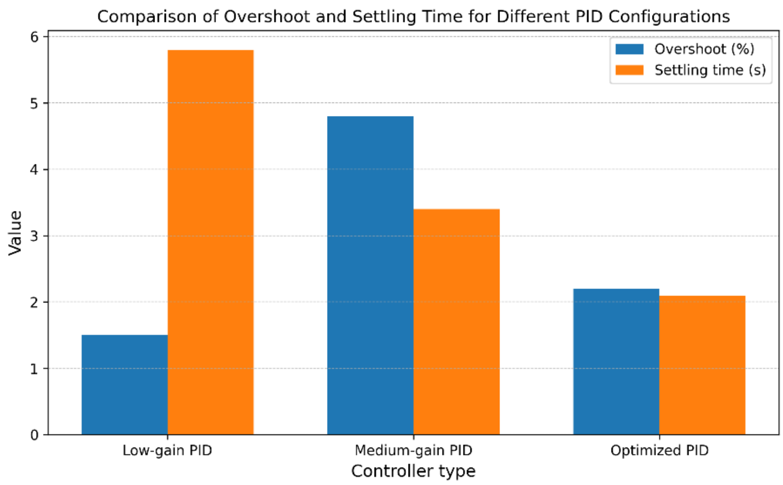

Figure 2
Comparison of overshoot and settling time for different PID configurations

The results show that the medium-gain PID controller produced the highest overshoot value, while the optimized PID controller-maintained overshoot at an acceptable level. Although the low-gain PID controller had relatively low overshoot, its settling time was significantly longer. Therefore, the low-gain configuration cannot be considered effective for fast UAV stabilization.

Stability comparison. The stability comparison was carried out by evaluating the response smoothness, convergence speed, and final error value. The optimized PID controller demonstrated the most stable response because it reached the reference angle faster and maintained the output close to the desired value.

Table 4
Stability comparison of PID configurations

Evaluation criterion	Low-gain PID	Medium-gain PID	Optimized PID
Response speed	Low	Medium	High
Overshoot level	Low	Medium	Low
Settling performance	Weak	Acceptable	Good

Steady-state accuracy	Medium	Good	High
Oscillation tendency	Low	Medium	Low
Overall stability	Acceptable	Good	High

The results confirm that proper PID parameter selection has a direct influence on UAV stabilization performance. Increasing the proportional gain improves response speed, but excessive values may increase overshoot. The integral gain reduces steady-state error, while the derivative gain improves damping and reduces oscillation. Therefore, balanced tuning of K_p, K_i, and K_d are necessary for reliable UAV flight control.

Overall, the optimized PID configuration demonstrated better stabilization performance than the low-gain and medium-gain configurations. It provided faster response, lower steady-state error, and more stable attitude control behavior.

Quantitative performance improvement assessment

In order to provide a quantitative comparison of the PID configurations, the performance improvement of the optimized PID controller was calculated relative to the low-gain PID controller. The improvement rate was determined using the following expression:

$$I_p = \frac{P_{low} - P_{opt}}{P_{low}} \times 100\% \qquad (15)$$

where I_p is the improvement percentage, P_{low} is the parameter value obtained for the low-gain PID controller, and P_{opt} is the corresponding parameter value obtained for the optimized PID controller.

Table 5

Quantitative improvement of optimized PID controller compared with low-gain PID

Performance parameter	Low-gain PID	Optimized PID	Improvement, %
Rise time, s	2.40	0.95	60.4
Settling time, s	5.80	2.10	63.8
Steady-state error, degree	0.42	0.05	88.1
Overshoot, %	1.5	2.2	-46.7

The calculation results show that the optimized PID controller reduced the rise time by 60.4%, settling time by 63.8%, and steady-state error by 88.1% compared with the low-gain PID controller. Although the overshoot value slightly increased, it remained within an acceptable stability range. Therefore, the optimized PID configuration demonstrated a more effective dynamic response and higher stabilization accuracy for UAV attitude control.

Discussion

The simulation results show that the optimized PID controller improves UAV stabilization compared with the low-gain and medium-gain configurations. As seen in Table 3 and Figures 1-2, it provides shorter settling time, lower steady-state error, and a more stable response. The PID controller affects the system through three main components: the proportional term increases response speed, the integral term reduces steady-state error, and the derivative term decreases oscillations. The controller is expressed as:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt} \qquad (16)$$

The results indicate that balanced selection of K_p, K_i, and $K_d$is important for stable UAV attitude control. However, fixed PID parameters may be less effective under nonlinear dynamics, payload changes, and external disturbances. Therefore, adaptive and AI-based tuning methods may be considered in future UAV control studies. Similar quadrotor flight dynamics and stabilization behavior were also discussed by Hoffmann et al. (2007).

Conclusion

This study examined the application of PID-based control for improving the stabilization performance of unmanned aerial vehicles. A simplified mathematical model of UAV attitude motion was developed for roll, pitch, and yaw channels, and the effect of PID parameters on the dynamic response of the system was evaluated through simulation.

The obtained results indicate that the selection of proportional, integral, and derivative coefficients has a direct influence on flight stability. In comparison with low-gain and medium-gain configurations, the optimized PID controller demonstrated shorter settling time, lower steady-state error, and smoother attitude response. The analysis also showed that the proportional term mainly improves response speed, the integral term compensates for steady-state error, and the derivative term contributes to damping and oscillation reduction.

Although PID control is a practical and computationally efficient method for UAV stabilization, its effectiveness depends strongly on parameter tuning. Fixed PID coefficients may not always provide the same performance under nonlinear flight dynamics, payload variation, or external disturbances. Therefore, further improvement of UAV control systems may require adaptive tuning strategies and intelligent optimization methods.

Overall, the study confirms that PID-based control can be effectively used for UAV attitude stabilization. Future research may focus on adaptive PID structures, fuzzy logic, neural-network-based controllers, and AI-assisted tuning approaches to increase control accuracy, robustness, and autonomous flight performance under more complex operating conditions.

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Yasamal Dist., Baku, Azerbaijan
Phone: +994 50 209 59 68
e-mail: info@aem.az