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Research paper

AI-Supported Learning and Academic Performance: The Mediating Role of Student Engagement

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ABSTRACT

Introduction
Artificial intelligence (AI) is increasingly integrated into higher education through intelligent tutoring systems, generative AI applications, adaptive learning platforms, automated feedback tools, and AI-supported academic resources. Although these technologies may facilitate personalized learning, improve access to information, and support academic tasks, their contribution to academic performance depends partly on how students engage with learning activities. Student engagement may therefore represent an important mechanism linking AI-supported learning with academic outcomes.
Objective
This study aims to examine the relationship between AI-supported learning and academic performance among university students, focusing on the mediating role of student engagement.
Methodology
A quantitative, non-experimental, cross-sectional correlational design is proposed. Data will be collected through a structured questionnaire administered to university students with experience using AI-supported learning tools. AI-supported learning will be assessed through dimensions such as frequency of use, perceived usefulness, personalization, feedback quality, and integration into academic activities. Student engagement will be examined through behavioral, cognitive, and emotional dimensions. Academic performance will be measured using students' reported academic outcomes and, where authorized and feasible, verified academic records. Descriptive statistics, reliability and validity assessments, regression analysis, and bootstrapped mediation analysis will be used to examine the proposed relationships.
Expected contribution
The study is designed to clarify whether student engagement helps explain the relationship between AI-supported learning and academic performance. It also seeks to distinguish technology use from meaningful learning participation, emphasizing that access to AI tools alone may not guarantee improved educational outcomes.
Conclusion
The proposed framework positions student engagement as a potential explanatory mechanism through which AI-supported learning may be associated with academic performance. The findings, once empirical data have been collected and analyzed, may inform universities seeking to integrate AI into teaching and learning in ways that promote active participation, critical thinking, and responsible technology use.

1.Introduction

Artificial intelligence (AI) is increasingly transforming higher education by changing how students access information, engage with learning materials, receive academic support, and develop knowledge and skills. AI-powered educational technologies, including intelligent tutoring systems, generative AI applications, adaptive learning platforms, and automated feedback tools, offer new opportunities to personalize instruction and support students with diverse educational needs. These technologies can facilitate independent learning, provide immediate explanations, and help students overcome academic difficulties. However, the benefits of AI-supported learning may not be distributed equally across student populations. Differences in access to digital infrastructure, technological resources, institutional support, and AI-related competencies may determine who can benefit most from these innovations.

Academic inequality remains a persistent challenge in higher education. Students from different socioeconomic backgrounds may experience unequal access to educational resources, academic support, and opportunities to develop the skills required for academic success. Although digital technologies have the potential to reduce some educational barriers, their implementation may also reproduce or intensify existing inequalities when access to technological resources and the capacity to use them effectively are unevenly distributed. In the context of AI-supported education, these differences may become particularly significant because students' ability to benefit from AI tools depends not only on whether such tools are available but also on their affordability, usability, reliability, and alignment with academic needs.

The growing availability of AI-based learning technologies introduces an important question concerning educational equity: can these tools reduce academic disparities, or might they create new forms of inequality among students? Students with reliable internet access, appropriate devices, paid AI subscriptions, digital literacy, and guidance from their educational institutions may be better positioned to integrate AI into their learning activities. Conversely, students with limited financial resources, inadequate technological infrastructure, or insufficient training may face barriers to effective adoption. These differences could influence the quality of academic assistance students receive, their ability to complete learning tasks efficiently, and their opportunities to develop competencies that contribute to academic performance.

Unequal access to learning enhancement technologies should therefore be understood as a multidimensional issue. Access involves more than the physical availability of digital tools; it also encompasses the affordability of advanced features, the quality of technological infrastructure, students' digital and AI literacy, the availability of institutional guidance, and their capacity to evaluate AI-generated information critically. Students may have access to the same applications but experience substantially different educational benefits because they differ in their knowledge, confidence, learning environments, and opportunities to use these technologies. Consequently, evaluating the relationship between artificial intelligence and academic inequality requires attention to both technological availability and the conditions that shape meaningful educational use.

This issue also has implications for universities and educational policymakers. Institutions are increasingly expected to integrate AI into teaching and learning while maintaining academic standards, promoting responsible technology use, and ensuring equitable educational opportunities. Without appropriate policies, AI adoption may advantage students who already possess greater resources and technological competencies. In contrast, initiatives that provide equitable access, AI literacy training, accessible digital infrastructure, and pedagogical guidance may help institutions ensure that AIsupported learning benefits a broader range of students. Understanding these dynamics is essential for developing educational strategies that promote innovation without reinforcing existing social and academic disadvantages.

Despite growing interest in AI-supported education, further investigation is needed into how inequalities in access to learning enhancement technologies relate to broader patterns of academic inequality in higher education. In particular, it is important to distinguish between access to AI tools, the ability to use them effectively, and the academic opportunities that may result from their use. Examining these dimensions together can provide a more comprehensive understanding of the mechanisms through which AI may influence educational equity. It can also help identify institutional and student-level factors that may mitigate unequal access and support more inclusive approaches to technological innovation.

Agains this background, this article examines how artificial intelligence may reshape academic inequality in higher education through unequal access to learning enhancement technologies. It focuses on the differences in technological access and use that may affect students' opportunities to benefit from AI-supported learning. The central objective is to analyze the relationship between access to AI-based educational resources and academic inequality, considering the potential role of socioeconomic conditions, digital competencies, and institutional support. By addressing these dimensions, the study aims to contribute to discussions on educational equity and the responsible integration of artificial intelligence into higher education.

The article is guided by the following research question: How does unequal access to AI-based learning enhancement technologies contribute to academic inequality in higher education? Addressing this question can help clarify whether disparities in technological access and effective use are associated with unequal academic opportunities and identify areas where universities may intervene to promote more equitable AI-supported learning environments.

2. Literature Review and Theoretical Framework

2.1. Artificial Intelligence in Higher Education

Artificial intelligence has become an increasingly significant component of higher education, offering new approaches to personalized instruction, academic assistance, information retrieval, and the development of learning resources. AI-based technologies, particularly generative AI systems, enable students to obtain explanations, explore complex concepts, organize information, receive writing assistance, and engage in self-directed learning. These capabilities have expanded the potential applications of AI beyond traditional educational software, positioning it as a flexible resource that students can incorporate into a wide range of academic activities.

However, the educational implications of AI depend on the conditions under which these technologies are accessed and used. The availability of AI applications does not necessarily guarantee equivalent educational benefits for all students. Differences in technological infrastructure, financial resources, digital competencies, and institutional guidance may influence the extent to which students can integrate AI into their academic practices. Consequently, AI adoption should be examined not only as a technological transformation but also as a process shaped by existing educational and social inequalities.

Recent research has begun to investigate these relationships directly. Zhang et al. (2024), for example, examined college students' digital literacy, AI literacy, ChatGPT activities, and educational outcomes from a digital divide perspective. Their findings suggest that socioeconomic status is associated with AI literacy and that different forms of ChatGPT use have different relationships with academic selfefficacy and creativity. This evidence indicates that the educational implications of AI cannot be adequately understood by considering technology use alone; researchers must also examine students' capabilities, patterns of use, and the circumstances in which AI is incorporated into learning.

Furthermore, AI technologies may provide substantial support to students who experience difficulties accessing conventional academic assistance. At the same time, their benefits may be constrained by subscription costs, inadequate connectivity, limited institutional support, and uncertainty regarding appropriate academic use. These considerations highlight the need to investigate the relationship between AI adoption and educational equity, particularly in higher education environments characterized by differences in socioeconomic resources and technological readiness

2.2. Academic Inequality in Higher Education

Academic inequality refers to differences in students' educational opportunities, access to learning resources, academic experiences, and outcomes. Although academic performance is influenced by individual characteristics and learning behaviors, it is also shaped by broader social, economic, institutional, and technological conditions. Students may enter higher education with different levels of prior preparation, access to academic support, financial stability, and opportunities to develop the competencies required for successful learning.

The digital transformation of education introduces an additional dimension to these inequalities. Students who have reliable internet access, suitable devices, and opportunities to develop advanced digital skills may be better positioned to take advantage of technologyenhanced learning environments. Conversely, students with limited technological resources may experience additional barriers when educational activities increasingly depend on digital platforms and online resources.

The emergence of generative AI raises further questions about how educational opportunities are distributed. AI applications can provide rapid explanations, writing support, and individualized assistance that might otherwise require substantial time or financial resources. Nevertheless, students do not necessarily possess equal opportunities to access these capabilities or use them effectively. As a result, the integration of AI into higher education may interact with existing inequalities in ways that depend on the availability of resources, institutional practices, and individual competencies.

Importantly, unequal academic outcomes should not automatically be attributed to differences in AI access. Academic performance is multidimensional and may be influenced by prior achievement, motivation, teaching quality, disciplinary requirements, and other contextual factors. Research examining AI-related academic inequality should therefore distinguish between unequal access to technological resources, differences in how students use those resources, and differences in educational outcomes.

This distinction is essential for determining whether AI technologies are associated with the reproduction of existing inequalities, the emergence of new forms of disadvantage, or the reduction of particular educational barriers.

2.3. The Digital Divide and Unequal Access to AI Technologies

The digital divide provides a useful theoretical perspective for understanding disparities in access to and use of AI-based learning technologies. Traditionally, digital inequality has been examined through differences in access to technological infrastructure, the skills required to use digital resources, and the benefits individuals obtain from technology use. These dimensions are particularly relevant to AIsupported education because meaningful participation requires more than the ability to open or access an application.

The first dimension concerns material access. Students may differ in their availability of computers, smartphones, stable internet connections, and compatible software. These resources influence whether students can use AI applications consistently and complete technology-dependent academic activities. Financial barriers may also affect access to advanced features, higher usage limits, or subscriptionbased services.

The second dimension concerns skills and competencies. Students with stronger digital and AI literacy may be better equipped to formulate effective prompts, assess the reliability of generated information, identify potential errors, and integrate AI-generated material into academic work. Students with limited AI literacy may experience difficulties obtaining useful responses or evaluating whether those responses are accurate and appropriate. Therefore, the educational value of AI may depend on the interaction between access and the competencies needed to use it effectively.

The third dimension concerns the outcomes of technology use. Even when students possess similar levels of access, they may differ in the academic benefits they obtain. Some may use AI to clarify concepts, identify knowledge gaps, and improve their understanding of course material. Others may rely on AI primarily to complete tasks without sufficiently engaging with the underlying concepts. Such differences suggest that technological access does not automatically translate into equivalent learning opportunities.

Recent research reinforces the relevance of these distinctions. Eddine et al. (2026) mapped evidence on generative AI and digital divide phenomena in higher education, identifying recurring concerns related to infrastructure, affordability, AI literacy, and institutional policy. The review also highlighted limitations in the existing evidence base, including uneven geographical coverage and a shortage of longitudinal studies and evaluations of equity-focused interventions.

Taken together, these findings support a multidimensional understanding of AI access. For the purposes of this study, access to AIbased learning enhancement technologies is conceptualized as a combination of material availability, affordability, digital and AI literacy, and institutional support.

This approach makes it possible to investigate inequalities in students' actual opportunities to benefit from AI rather than treating access as a simple binary condition

2.4. Socioeconomic Status and Unequal Opportunities for AI-Supported Learning

Socioeconomic status is an important contextual factor in understanding students' access to educational resources. Differences in household income, financial security, and access to educational support may influence students' ability to obtain suitable devices, maintain reliable internet connectivity, and use digital services without interruption.

In the context of AI-supported learning, these differences may affect both the frequency and the quality of technology use. Students with greater financial resources may be more able to afford advanced AI subscriptions, access multiple digital learning platforms, and participate in supplementary training. Students with fewer resources may depend on free versions of applications, shared devices, limited mobile data, or intermittent internet connections. Such constraints may reduce the continuity and flexibility of their engagement with AI-based learning tools.

Nevertheless, socioeconomic status should not be understood as a direct or deterministic explanation of academic performance. Students from different economic backgrounds may develop effective learning strategies, receive support from peers, or benefit from institutional initiatives that reduce technological barriers. Likewise, financial resources alone do not guarantee high levels of AI literacy or effective educational use.

The relationship between socioeconomic status and AI-supported learning is therefore likely to depend on additional conditions, including digital competencies, institutional support, and the availability of accessible learning resources. Examining these factors together can help clarify how socioeconomic differences may influence students' opportunities to benefit from AI technologies.

2.5. AI Literacy and the Effective Use of Learning Enhancement Technologies

AI literacy refers to the knowledge, skills, and critical judgment required to understand, interact with, evaluate, and responsibly use artificial intelligence systems. In higher education, AI literacy is particularly important because students must determine how to formulate requests, assess generated information, recognize possible inaccuracies or biases, and use AI outputs in accordance with academic expectations.

The relationship between AI literacy and academic opportunity extends beyond technical proficiency. Students need to understand that AI-generated responses may contain errors, omit relevant information, or present uncertain claims with apparent confidence. They must also be able to compare generated content with reliable sources and retain responsibility for the accuracy and integrity of their academic work.

Differences in AI literacy may contribute to unequal outcomes even when students have access to the same technological tools. Students who can critically evaluate and adapt AI-generated information may be better positioned to use it as a resource for learning. In contrast, students who lack these competencies may be more vulnerable to misinformation, inappropriate reliance on automated outputs, or ineffective use of available tools.

Zhang et al. (2024) provide relevant evidence by examining the relationships among socioeconomic status, digital and AI literacy, patterns of ChatGPT use, and educational outcomes. Their study emphasizes the importance of distinguishing between different types of AI use and considering the role of trust in shaping the relationship between AI-supported activities and student outcomes.

Accordingly, AI literacy is treated in this study as a potential explanatory factor in the relationship between access to AI technologies and academic inequality. It may help explain why access to similar tools does not necessarily produce equivalent educational benefits across student groups.

2.6. Institutional Support and Educational Equity

Higher education institutions play an important role in determining how students encounter and use AI technologies. Institutional policies, digital infrastructure, training opportunities, academic guidance, and access to educational resources can influence students' ability to incorporate AI into their learning practices.

Institutions that provide accessible AI tools and structured training may reduce barriers associated with financial resources and prior technological experience. Clear guidance can also help students distinguish appropriate academic assistance from practices that undermine independent learning or violate academic integrity requirements. These measures may be especially important for students who have limited opportunities to develop AI literacy independently.

Conversely, institutions that adopt AI technologies without considering accessibility, affordability, and differences in student preparedness may unintentionally create unequal learning conditions. For example, when assignments implicitly assume that students possess advanced technological resources or competencies, those with limited access may face additional disadvantages.

Institutional support should therefore be considered an important contextual dimension of AI-related educational inequality. Its influence may extend beyond providing access to specific applications to include the creation of inclusive learning environments, the development of responsible-use guidelines, and the provision of academic support for students with different needs.

From an educational equity perspective, the objective is not simply to increase AI adoption but to ensure that students have meaningful opportunities to benefit from AI-supported learning. This requires institutions to consider the distribution of resources, the accessibility of technologies, and the development of the competencies necessary for effective and responsible use.

2.7. Theoretical Framework: Digital Inequality and the Unequal Distribution of Educational Benefits

This study draws primarily on the digital divide and digital inequality perspective to explain how differences in access to AI-based learning enhancement technologies may contribute to academic inequality in higher education. The framework recognizes that technological disparities involve multiple interconnected dimensions, including material access, digital competencies, patterns of use, and the outcomes obtained from technology use.

Within this framework, unequal access is not limited to whether a student can use an AI application. It also encompasses the affordability of relevant services, the availability of reliable technological infrastructure, the ability to use AI effectively, and the institutional conditions that support or constrain its educational application.

The study further incorporates socioeconomic status and institutional support as contextual factors that may shape these relationships. Socioeconomic resources may influence students' access to devices, connectivity, and paid services, while institutional support may facilitate access and strengthen AI literacy. AI literacy, in turn, may influence how effectively students transform technological access into meaningful learning opportunities.

The proposed conceptual relationship can be summarized as follows:

Socioeconomic conditions may shape students' opportunities to access AI-based learning technologies.

Access to AI technologies may influence the frequency, continuity, and range of students' AI-supported learning activities.

AI literacy may affect students' capacity to use these technologies critically, effectively, and responsibly.

Institutional support may facilitate more equitable access and help students develop the competencies required for effective use.

Academic inequality may emerge or persist when differences in access, competencies, and institutional opportunities translate into unequal educational experiences or outcomes.

These relationships constitute a conceptual framework rather than established causal findings. Their strength and direction must be evaluated through empirical investigation that accounts for relevant student characteristics and institutional conditions.

2.8. Research Gap and Contribution of the Study

Existing research has established the relevance of digital inequality to the adoption and use of generative AI in higher education. Studies have examined relationships among socioeconomic status, AI literacy, patterns of ChatGPT use, and educational outcomes, while recent reviews have identified affordability, infrastructure, competencies, and institutional policies as recurring concerns.

Nevertheless, important questions remain regarding how these dimensions interact and how their relationships can be examined within a coherent framework of academic inequality. In particular, the distinction between access to AI technologies and the capacity to use them effectively requires further attention. Simply measuring whether students use AI may overlook differences in the quality of access, the competencies available to them, and the academic benefits they obtain.

There is also a need for research that considers institutional support alongside student-level characteristics. Universities may influence AIrelated inequalities through their technological infrastructure, training opportunities, accessibility policies, and guidance on responsible use. Investigating these contextual conditions may help identify opportunities to reduce barriers and promote more inclusive AIsupported learning environments.

The present study addresses these issues by examining unequal access to AI-based learning enhancement technologies as a potential contributor to academic inequality in higher education. Its proposed contribution is to bring together material access, socioeconomic conditions, AI literacy, and institutional support within a single analytical framework. This framework is intended to support a more comprehensive assessment of how differences in technological opportunities may relate to unequal academic experiences and outcomes.

The study therefore seeks to move beyond a general discussion of AI's educational potential and examine the conditions under which its benefits may be distributed unequally. By distinguishing access, effective use, and academic outcomes, it aims to provide a basis for empirical research and for the development of institutional strategies that promote educational equity in the context of AI integration.

3. Research Hypotheses And Conceptual Model

3.1. General Objective

The general objective of this study is to examine how unequal access to artificial intelligence (AI)-based learning enhancement technologies may contribute to academic inequality in higher education, considering the roles of socioeconomic conditions, AI literacy, and institutional support.

3.2. Specific Objectives

To achieve the general objective, the study establishes the following specific objectives:

1. To assess differences in students' access to AI-based learning enhancement technologies according to their socioeconomic characteristics and technological resources.
2. To examine the relationship between access to AI-based learning enhancement technologies and academic outcomes among higher education students.
3. To analyze the role of AI literacy in explaining differences in students' capacity to use AI technologies effectively for academic purposes.
4. To investigate whether institutional support is associated with more equitable access to and use of AI-based learning enhancement technologies.
5. To develop an integrated analytical framework for understanding how disparities in technological access, AI literacy, and institutional support may be associated with academic inequality in higher education.

3.3. Research Questions

The study is guided by the following research questions:

RQ1. To what extent does access to AI-based learning enhancement technologies differ among higher education students according to their socioeconomic characteristics and technological resources?

RQ2. What is the relationship between students' access to AI-based learning enhancement technologies and their academic outcomes?

RQ3. How is AI literacy associated with students' ability to use AI technologies effectively for academic purposes?

RQ4. What role does institutional support play in the relationship between AI access and academic inequality?

RQ5. How can socioeconomic conditions, technological access, AI literacy, and institutional support be integrated into a framework for analyzing academic inequality in AI-supported higher education?

3.4. Research Hypotheses

Drawing on the digital inequality perspective and the literature on AIsupported education, this study proposes the following hypotheses for empirical examination.

H1. Socioeconomic Conditions and AI Access

H1: Students' socioeconomic conditions are significantly associated with their access to AI-based learning enhancement technologies.

This hypothesis proposes that differences in financial resources and access to technological infrastructure may be associated with differences in students' opportunities to use AI applications for academic purposes.

H2. AI Access and Academic Outcomes

H2: Access to AI-based learning enhancement technologies is significantly associated with academic outcomes among higher education students.

This hypothesis examines whether differences in access to AIsupported educational resources are related to differences in academic outcomes. The direction and magnitude of this relationship must be established through empirical analysis rather than assumed in advance.

H3. AI Literacy and Effective Technology Use

H3: Higher levels of AI literacy are positively associated with students' effective use of AI-based learning enhancement technologies for academic purposes.

This hypothesis proposes that students who can formulate appropriate prompts, critically evaluate AI-generated information, and integrate AI outputs responsibly may be better positioned to use these technologies as learning resources.

H4. Institutional Support and Equitable AI Access

H4: Institutional support is positively associated with equitable access to and effective use of AI-based learning enhancement technologies among higher education students.

This hypothesis examines whether institutional initiatives, including AI literacy training, accessible technological infrastructure, and clear guidance on responsible AI use, are associated with more equitable opportunities to benefit from AI-supported learning.

H5. AI Literacy as a Potential Explanatory Mechanism

H5: AI literacy statistically accounts for part of the relationship between access to AI-based learning enhancement technologies and academic outcomes.

This hypothesis examines whether differences in AI literacy may help explain the association between technological access and academic outcomes. Testing this hypothesis requires an appropriate mediation analysis and evidence that the proposed relationships are supported by the collected data.

3.5. Conceptual Model

Based on the theoretical framework, the proposed model includes four principal dimensions: socioeconomic conditions, access to AI-based learning enhancement technologies, AI literacy, and institutional support. Academic outcomes constitute the principal educational outcome, while academic inequality is examined through differences in access, use, and outcomes across student groups.

The conceptual relationships are organized as follows:

- Socioeconomic conditions → AI access: Socioeconomic resources may be associated with students' opportunities to access devices, connectivity, and AI services.
- AI access → Academic outcomes: Access to AI-based learning resources may be associated with academic outcomes.
- AI literacy → Effective AI use: AI literacy may influence students' capacity to use AI technologies critically and effectively.
- Institutional support → AI access and effective use: Institutional resources and guidance may help reduce barriers to access and strengthen students' AI competencies.
- AI access → AI literacy → Academic outcomes: AI literacy may account for part of the association between access to AI technologies and academic outcomes.

These relationships provide a preliminary analytical structure for the study. They do not establish causal effects. Their validity must be assessed using an appropriate research design, operational definitions, and empirical evidence.

3.6. Expected Theoretical Contribution

The proposed study seeks to contribute to research on educational equity by examining AI access as a multidimensional phenomenon rather than a simple measure of technology availability. It distinguishes between material access, the competencies required to use AI effectively, institutional support, and the academic outcomes associated with technology use.

By integrating these dimensions, the study aims to clarify how differences in technological opportunities may be associated with academic inequality in higher education. The resulting framework may also help identify areas for institutional intervention, particularly in relation to affordable access, AI literacy development, and inclusive educational policies.

The proposed contribution is therefore both analytical and practical: to provide a structured basis for investigating unequal opportunities in AI-supported learning and to inform strategies intended to promote more equitable educational environments.

4. Methodology

4.1. Research Design

This study adopts a quantitative research approach to examine the relationship between unequal access to artificial intelligence (AI)-based learning enhancement technologies and academic inequality in higher education. The proposed design is non-experimental, cross-sectional, and correlational. This approach allows the investigation of differences in technological access, AI literacy, institutional support, and academic outcomes among higher education students without manipulating the conditions under which they use AI technologies.

A quantitative approach is appropriate because the study seeks to measure the dimensions associated with AI access and examine their statistical relationships with educational outcomes. The nonexperimental design enables the analysis of naturally occurring differences among students, while the cross-sectional component allows information to be collected within a defined period.

The study is guided by a multidimensional conceptual framework in which socioeconomic conditions, access to AI-based learning technologies, AI literacy, and institutional support are examined in relation to academic outcomes and educational inequality. The analysis will distinguish between the availability of AI tools, students' capacity to use them effectively, and the academic outcomes associated with their use.

Because the proposed design is cross-sectional and observational, the findings will be interpreted in terms of associations rather than definitive causal effects. Any claims concerning the mechanisms through which AI access may contribute to academic inequality will be evaluated in light of the study design and the available evidence.

4.2. Study Population and Sampling Strategy

The target population consists of students enrolled in higher education institutions who have opportunities to access or use AI-based learning enhancement technologies for academic purposes.

The study may include students from different academic disciplines, educational institutions, and socioeconomic backgrounds to capture variation in access to digital resources and opportunities for AIsupported learning.

The final sample size, participating institutions, geographical scope, and sampling strategy must be established before data collection. These decisions should reflect the size and characteristics of the target population, the expected magnitude of the relationships under investigation, the planned statistical analyses, and the feasibility of recruiting participants.

Where a complete sampling frame is available, a probability-based sampling strategy may be considered to improve representativeness. If access to the target population is limited, a non-probability sampling strategy may be more feasible; however, its limitations for generalizing findings should be explicitly acknowledged.

The study will document relevant participant characteristics, including age group, academic level, field of study, socioeconomic indicators, availability of technological resources, and previous experience with AI-based educational applications.

Information to be completed before submission:

- Country and geographical setting of the study.
- Participating universities or higher education institutions.
- Target population and eligibility criteria.
- Planned and final sample size.
- Sampling technique and recruitment procedure.
- Data collection period.

No specific sample size or participating institution is assumed in this manuscript because these details have not yet been provided.

4.3. Data Collection Instrument

Data will be collected using a structured questionnaire designed to measure the principal dimensions of the proposed conceptual framework. The questionnaire will include sections addressing participants' background characteristics, access to AI technologies, AI literacy, institutional support, patterns of AI use, and academic outcomes.

Where possible, the instrument should incorporate previously validated measurement scales relevant to digital inequality, AI literacy, technology use, and educational experiences. Any adaptation of existing measures should be documented, and the wording of items should be reviewed to ensure that they are appropriate for the target population and the higher education context.

The proposed questionnaire will include the following dimensions.

4.3.1. Socioeconomic Conditions

This dimension will capture relevant indicators of students' socioeconomic circumstances and access to educational resources. Potential indicators include perceived financial constraints, availability of personal devices, internet connectivity, and access to paid educational technologies.

Sensitive socioeconomic information should be collected only when necessary for the research objectives. Questions should be designed to minimize participant discomfort and protect confidentiality.

4.3.2. Access to AI-Based Learning Enhancement Technologies

Access will be measured through indicators addressing the availability, affordability, accessibility, and continuity of students' access to AI-based learning tools.

Potential indicators include:

- Availability of a suitable device for academic AI use.
- Reliability of internet connectivity.
- Ability to access AI applications when needed.
- Financial barriers to accessing advanced AI features.
- Availability of AI tools through the educational institution.
- Frequency of access to AI-based learning resources.

These indicators will help distinguish between basic access to technology and the conditions required for sustained educational use.

4.3.3. AI Literacy

AI literacy will be assessed through items addressing students' perceived ability to interact with AI systems, formulate effective prompts, evaluate generated information, identify potential inaccuracies, and use AI responsibly in academic contexts.

The questionnaire should distinguish between self-reported confidence and demonstrated competence wherever feasible. Self-reported measures can capture students' perceptions of their abilities, but they should not automatically be interpreted as objective assessments of AI literacy.

4.3.4. Institutional Support

Institutional support will be measured through indicators reflecting the extent to which students perceive their educational institutions as providing the resources and guidance required for effective and equitable AI use.

Potential indicators include access to digital infrastructure, AI-related training, guidance on responsible AI use, availability of technical assistance, and the clarity of institutional policies concerning AIsupported learning.

4.3.5. Academic Outcomes

Academic outcomes will be measured using an explicitly defined indicator appropriate to the study's objectives and the data available.

Potential measures include students' self-reported academic performance, course grades obtained with appropriate authorization, perceived academic effectiveness, or other validated educational indicators.

These measures should not be treated as interchangeable. If official grades are unavailable, self-reported academic performance may be used, provided that its limitations are acknowledged. The selected outcome measure must be specified before the final analysis.

4.3.6. Patterns of AI Use

The questionnaire will also assess how students incorporate AI into their academic activities. Relevant indicators may include frequency of use, purposes of use, types of applications accessed, and the extent to which AI is used to support understanding, practice, research, writing, or task completion.

Distinguishing between different patterns of AI use is important because frequency alone does not establish whether students use AI effectively or obtain meaningful educational benefits.

4.4. Measurement and Operationalization of Variables

The operationalization of the principal variables will be guided by the theoretical framework and the research hypotheses.

The main explanatory variable is access to AI-based learning enhancement technologies. Academic outcomes constitute the principal educational outcome, while socioeconomic conditions, AI literacy, and institutional support are examined as additional explanatory or contextual variables.

4.5. Instrument Validity and Reliability

The questionnaire should undergo a validation process before it is used for the principal data collection.

First, content validity may be assessed through expert review. Experts in educational research, digital technologies, AI literacy, and quantitative methodology may evaluate the relevance, clarity, and comprehensiveness of the proposed items.

Second, a pilot study may be conducted with participants who resemble the target population. The pilot will help identify ambiguous questions, assess completion time, evaluate response options, and determine whether the proposed measurement items function as intended.

Third, internal consistency should be assessed for multi-item scales where appropriate. Cronbach's alpha or McDonald's omega may be reported, depending on the measurement structure and analytical approach. Reliability coefficients should be calculated from the actual data rather than assumed in advance.

If the study uses established scales, their original validation evidence and any modifications made for the current context should be documented. Where the sample size and measurement structure permit, exploratory or confirmatory factor analysis may be considered to examine the dimensionality of the instrument.

These procedures are intended to strengthen the credibility of the measurement process. They do not guarantee validity, and the final manuscript should report only the procedures that were actually conducted and the results obtained

4.6. Data Collection Procedure

Data collection will proceed through a structured sequence of activities.

First, the research team will finalize the questionnaire, establish the eligibility criteria, and obtain the institutional permissions and ethical approvals required for the study.

Second, the questionnaire will undergo expert review and, where feasible, pilot testing. Revisions will be made to improve clarity and ensure that the instrument reflects the study's conceptual framework.

Third, eligible students will be invited to participate through the approved recruitment channels. Participants will receive information about the study's purpose, the voluntary nature of participation, the handling of their information, and their right to discontinue participation where applicable.

Fourth, questionnaire responses will be collected using the approved data collection method. Procedures will be implemented to minimize duplicate submissions, incomplete records, and inconsistencies in responses.

Finally, the collected data will be reviewed, coded, and prepared for statistical analysis. The research team will document the number of participants invited, the number of responses received, exclusions applied, and the final number of observations included in each analysis.

The actual data collection period, recruitment channels, and final participant numbers must be reported once the procedure has been completed.

4.7. Data Analysis Strategy

Data analysis will be conducted in stages, with the specific procedures determined by the measurement properties of the variables and the final research questions.

4.7.1. Preliminary Data Screening

The initial stage will examine missing values, duplicate responses, inconsistent entries, and potential outliers. The extent and pattern of missing data will be assessed before decisions are made regarding exclusion or imputation.

The analysis will also consider whether the measurement variables satisfy the assumptions of the statistical procedures selected for the study.

4.7.2. Descriptive Statistics

Descriptive statistics will be used to summarize participants' characteristics and the principal study variables.

Frequencies and percentages will be reported for categorical variables. Means and standard deviations or medians and interquartile ranges will be used for numerical variables, depending on their distributions.

These analyses will provide an overview of students' access to AI technologies, AI literacy, institutional support, patterns of AI use, and academic outcomes.

4.7.3. Group Comparisons

To examine potential inequalities in access and academic outcomes, comparisons may be conducted across predefined socioeconomic groups or groups with different levels of technological access.

The selection of statistical tests will depend on the measurement scale, distribution of the data, independence of observations, and relevant assumptions.

Where appropriate, effect sizes and confidence intervals will be reported alongside statistical significance to indicate the magnitude and precision of observed differences.

4.7.4. Association Analysis

Correlation analyses will be used to examine the relationships among AI access, AI literacy, institutional support, socioeconomic conditions, and academic outcomes.

Pearson's correlation may be appropriate for variables meeting its assumptions, while Spearman's rank correlation may be more suitable for ordinal or non-normally distributed variables.

These analyses will provide an initial assessment of the direction and strength of associations but will not establish causal relationships.

4.7.5. Multivariable Analysis

Multivariable regression may be used to examine whether AI access is associated with academic outcomes after accounting for relevant student characteristics and contextual factors.

The choice of regression model will depend on the operational definition of the outcome variable. Linear regression may be appropriate for a sufficiently continuous outcome, while ordinal or logistic regression may be required for categorical outcomes.

Potential covariates include prior academic achievement, academic level, field of study, socioeconomic indicators, and institutional context, provided that they are measured reliably and justified theoretically.
The analysis should assess relevant model assumptions, potential multicollinearity, and the influence of clustering when students are sampled from multiple institutions.

4.7.6. Mediation Analysis

Mediation analysis may be conducted to investigate whether AI literacy statistically accounts for part of the relationship between AI access and academic outcomes.
In a simple mediation model, AI access is represented as the predictor, AI literacy as the proposed mediator, and academic outcomes as the outcome variable.
The indirect association may be estimated as the product of the path from AI access to AI literacy and the path from AI literacy to academic outcomes, conditional on AI access and any justified covariates.
Bootstrap confidence intervals may be used to evaluate the indirect effect, provided that the sample size and analytical assumptions are adequate.
Because the proposed study is cross-sectional, any indirect effect will be interpreted as a statistical mediation pattern rather than conclusive evidence of a causal mechanism. Stronger causal conclusions would require an appropriate temporal design and additional assumptions.

4.7.7. Statistical Reporting

The final manuscript will report the statistical methods actually used, the relevant test statistics, effect sizes, confidence intervals, and exact p-values where appropriate.
The significance threshold, if used, will be specified before the principal analysis. Results will be interpreted in relation to the research questions and hypotheses, considering both statistical and practical significance.
No numerical results are reported in this section because the study data have not been provided.

4.8. Ethical Considerations

The study will follow applicable ethical standards for research involving human participants and the requirements of the participating institution or institutions.
Participation will be voluntary, and prospective participants will receive clear information about the research objectives, the information being collected, and the intended use of the data. Informed consent will be obtained in accordance with the applicable ethical requirements.
The research team will implement appropriate measures to protect participants' confidentiality and personal information. Data collection instruments should avoid collecting directly identifying information unless it is necessary and explicitly justified. Access to research data will be restricted to authorized personnel, and the data will be stored and retained according to the approved research protocol and applicable data protection requirements.
Because the study concerns AI use in academic settings, the questionnaire should be designed to avoid unnecessarily collecting students' AI conversation histories, private prompts, account credentials, or other sensitive information unrelated to the research objectives.
The final manuscript must identify the relevant ethics committee or institutional review process and report the approval number or exemption status where applicable. Such details should be included only after the corresponding determination has been obtained.

4.9. Methodological Limitations

Several methodological limitations should be considered when interpreting the findings.
First, a cross-sectional design provides information about relationships observed at a particular point in time but does not establish temporal ordering or causality.
Second, self-reported measures of AI use, AI literacy, and academic performance may be affected by recall errors, social desirability, or differences in participants' interpretation of questionnaire items.
Third, a non-probability sample, if used, may limit the generalizability of the findings beyond the participating students and institutions.
Fourth, AI technologies evolve rapidly, meaning that students' access and use patterns may change as applications, institutional policies, and pricing models change.
Finally, academic inequality is a multidimensional phenomenon that cannot necessarily be captured by a single indicator. The study will therefore distinguish between unequal technological access, differences in effective use, and differences in academic outcomes wherever the available data permit.
These limitations will be considered when discussing the results and developing recommendations for higher education institutions and educational policymakers.

5. Results

5.1. Participant Characteristics and Descriptive Analysis

The first stage of the analysis will describe the characteristics of the participating students and establish the empirical context for examining inequalities in access to artificial intelligence (AI)-based learning enhancement technologies. The analysis will consider relevant sociodemographic, socioeconomic, and academic characteristics, including age, gender, academic level, field of study, socioeconomic background, and previous experience with digital learning resources.
Particular attention will be given to differences in students' technological circumstances. The availability of personal devices, the reliability of internet connectivity, the affordability of digital services, and previous experience with AI applications may influence students' opportunities to participate in AI-supported learning. Examining these characteristics will help determine whether the study population includes students with diverse levels of technological access and educational resources.
Descriptive statistics will also be used to characterize the principal study variables, including access to AI technologies, AI literacy, institutional support, patterns of AI use, and academic outcomes. Frequencies and percentages will be calculated for categorical variables, while appropriate measures of central tendency and variability will be used for continuous or composite measures.
The analysis will additionally examine the completeness and quality of the collected data. Missing responses, inconsistent entries, and potential response biases will be assessed before conducting the principal statistical analyses. The final report will specify the number of participants included in each analysis and explain any exclusions applied during data preparation.
This initial stage will provide the foundation for interpreting the subsequent findings. In particular, it will establish the characteristics of the population in which the relationships between AI access and academic inequality are examined, helping readers assess the relevance and potential generalizability of the results.

5.2. Distribution of Access to AI-Based Learning Enhancement Technologies

The second stage will examine the extent to which students have access to AI-based learning enhancement technologies and the conditions under which they can use these resources for academic purposes. Access will be considered a multidimensional construct involving technological availability, affordability, connectivity, continuity of access, and opportunities to use AI applications through institutional resources.
The analysis will first establish whether students have access to suitable devices and reliable internet connections. These resources constitute important conditions for using AI applications consistently. Students who rely on shared devices, limited mobile data, or unstable internet connections may experience interruptions that constrain their ability to incorporate AI into academic activities.
The analysis will also investigate differences between access to free AI applications and access to paid services or advanced features. Although some AI tools are available without a subscription, differences in usage limits, functionality, and availability may create unequal opportunities to obtain educational assistance. These differences should be examined empirically rather than assuming that paid services necessarily produce superior academic outcomes
Institutional access will constitute another important dimension. Some students may benefit from AI tools, digital learning platforms, or training opportunities provided by their universities, whereas others may depend primarily on resources they obtain independently. Examining these conditions will help establish whether institutional provision is associated with differences in students' opportunities to use AI for academic purposes.
The analysis will further distinguish between nominal access and meaningful access. Nominal access refers to the ability to reach or use an AI application, whereas meaningful access involves having the resources, competencies, and opportunities necessary to incorporate the technology into learning activities. This distinction is important because the presence of an AI application on a student's device does not necessarily indicate that the student can use it consistently or effectively.
The resulting descriptive findings will provide an overview of the distribution of AI access among the participating students. They will also help identify the most relevant barriers to further investigation, including financial constraints, technological limitations, and differences in institutional provision.

5.3. Socioeconomic Differences in Access to AI Technologies

The third stage will examine whether students' access to AI-based learning enhancement technologies differs across socioeconomic groups. This analysis will address the possibility that financial and material circumstances are associated with unequal opportunities to use AI in higher education.
Relevant socioeconomic indicators may include perceived financial constraints, device ownership, internet affordability, access to paid digital services, and the availability of educational resources outside the university. The analysis will assess whether these characteristics are associated with differences in students' reported access to AI technologies.
Comparisons between socioeconomic groups will be conducted using statistical procedures appropriate to the measurement properties of the variables. Where relevant, the analysis will report effect sizes and confidence intervals in addition to statistical significance. This approach will help distinguish between differences that are statistically detectable and differences that may be practically meaningful for educational policy.
The analysis will also consider the possibility that socioeconomic conditions are related to several dimensions of access simultaneously. For example, financial constraints may be associated with the availability of suitable devices, the stability of internet connectivity, and the ability to use subscription-based applications. Examining these dimensions separately and, where justified, jointly may provide a more comprehensive understanding of the relationship between socioeconomic circumstances and AI access.
However, socioeconomic differences should not be interpreted as deterministic explanations of students' technological opportunities. Institutional resources, family support, public digital infrastructure, and individual strategies may reduce or modify the barriers associated with limited financial resources. Accordingly, the analysis will consider socioeconomic conditions alongside other measured characteristics rather than attributing all observed differences to income or financial status alone.
The findings from this stage will provide evidence relevant to the first research hypothesis concerning the relationship between socioeconomic conditions and AI access. Whether the hypothesis receives support will depend on the observed associations, their magnitude, their uncertainty, and the analytical criteria established before the study is conducted.

5.4. AI Literacy and Patterns of Educational Technology Use

The fourth stage will examine students' AI literacy and the ways in which they incorporate AI technologies into their academic activities. This analysis is important because access to AI does not automatically translate into effective learning support. Students may differ substantially in their ability to formulate appropriate prompts, assess the credibility of generated information, identify inaccuracies, and integrate AI-generated material into their academic work.
AI literacy will be assessed using the measures selected for the study. If the questionnaire relies on self-reported items, the findings will describe students' perceived competencies rather than objectively demonstrated skills. If performance-based assessments are included, the analysis may additionally examine students' demonstrated ability to evaluate AI-generated content and use AI tools appropriately.
The analysis will also investigate students' purposes for using AI. These may include clarifying complex concepts, summarizing information, generating ideas, practicing problem-solving, obtaining feedback, supporting research activities, and improving the organization of academic work. The frequency of these activities will be examined alongside students' reported competencies and access conditions.
Distinguishing between different purposes of AI use is necessary because the frequency of use alone does not establish educational effectiveness. Students who use AI frequently may employ it in ways that support understanding and independent learning, while others may use it primarily to obtain answers without critically evaluating the information provided. These different patterns may have different relationships with academic outcomes.
The analysis will also consider students' ability to evaluate the limitations of AI-generated information. AI systems may produce inaccurate statements, incomplete explanations, or content that does not adequately reflect the requirements of a particular academic task. Students' ability to recognize and address these limitations may influence the quality of their educational use.
The results will therefore help establish whether students' reported AI literacy and patterns of use vary across the study population. They will also provide the basis for examining the proposed relationship between AI literacy and effective AI use, while recognizing that the strength of this relationship must be established through empirical evidence.

5.5. Institutional Support and Opportunities for Equitable AI Use

The fifth stage will examine the institutional conditions that may facilitate or constrain students' access to AI-based learning enhancement technologies. Universities influence the educational use of AI through their digital infrastructure, training opportunities, technical assistance, academic policies, and guidance on responsible technology use.
The analysis will assess students' reported access to institutionally provided resources and their perceptions of the support available for AI-supported learning. Relevant indicators may include the availability of AI literacy workshops, access to digital learning platforms, clarity of institutional guidelines, and opportunities to obtain assistance when technological difficulties arise.
Institutional support may be particularly relevant for students who have limited opportunities to develop AI competencies independently. Structured training and accessible guidance may help students understand how to formulate effective prompts, evaluate generated information, recognize limitations, and use AI in accordance with academic expectations.
The analysis will also examine whether students report different levels of support across institutions or academic contexts, where the sample and research design permit such comparisons. These differences may provide insight into the extent to which institutional

practices are associated with students' opportunities to access and use AI technologies.
Nevertheless, institutional support should not be interpreted solely through students' general perceptions of their universities. Where possible, perceived support should be distinguished from objectively documented institutional resources and policies. This distinction will help clarify whether the study measures the existence of institutional provision, students' awareness of that provision, or their actual ability to benefit from it.
The findings will contribute to the evaluation of the hypothesis concerning institutional support and equitable AI access. They may also help identify institutional practices that warrant further investigation as potential strategies for reducing disparities in AI-supported learning.

5.6. Relationships Between AI Access, AI Literacy, Institutional Support, and Academic Outcomes

The sixth stage will examine the relationships among the principal variables included in the conceptual framework. Correlation analyses and other appropriate statistical procedures will be used to investigate whether differences in AI access, AI literacy, socioeconomic conditions, and institutional support are associated with differences in academic outcomes.
The analysis will begin by examining the association between access to AI-based learning enhancement technologies and academic outcomes. Depending on the selected outcome measure, academic performance may be represented by course grades, an appropriately defined self-reported performance indicator, or another educational measure established before data collection.
The analysis will then examine the relationship between AI literacy and academic outcomes. Students who can evaluate AI-generated information and integrate it critically into their learning activities may be better positioned to obtain educational benefits from these technologies. However, the direction and magnitude of this relationship must be established empirically, as AI literacy may also be associated with other factors, including prior academic achievement and general digital competence.
Institutional support will be examined in relation to both AI access and AI literacy. If the data indicate that institutional support is associated with these variables, the findings may suggest that educational institutions have an important role in shaping students' opportunities to benefit from AI. Nevertheless, the analysis must distinguish observed associations from causal effects.
The study will also consider socioeconomic conditions when examining these relationships. This is important because an apparent association between AI access and academic outcomes may partly reflect differences in financial resources, prior educational opportunities, or other characteristics of the students.
Where appropriate, multivariable regression models will be used to examine whether associations remain after accounting for relevant covariates. The selection of covariates will be guided by the conceptual framework and the availability and quality of the collected data. The final analysis will report the estimated associations, confidence intervals, relevant statistical tests, and model diagnostics.
The interpretation will emphasize the magnitude and precision of the observed relationships rather than relying exclusively on statistical significance. This approach will help determine whether the evidence is consistent with the proposed conceptual framework and identify areas where further research is required.

5.7. Multivariable Analysis of Academic Outcomes

The seventh stage will use multivariable analysis, where appropriate, to examine the relationship between access to AI-based learning enhancement technologies and academic outcomes while accounting for relevant student characteristics.
The specific model will depend on the operational definition and distribution of the academic outcome. For example, a linear regression model may be appropriate when the outcome is sufficiently continuous and the relevant assumptions are adequately satisfied. If the outcome is ordinal or categorical, a different regression model may be more suitable.
The principal predictor will be the selected measure of AI access. Additional predictors may include AI literacy, institutional support, socioeconomic indicators, academic level, field of study, and prior academic achievement, provided that these variables are measured adequately and justified theoretically.
The analysis will assess whether the estimated association between AI access and academic outcomes changes when relevant covariates are included. A change in the estimated coefficient may indicate that the relationship is partly associated with other measured characteristics. However, such changes do not necessarily identify a causal mechanism, particularly in a cross-sectional observational study.
The model will also be assessed for relevant statistical assumptions, potential multicollinearity, influential observations, and other diagnostic considerations. If students are sampled from multiple universities or classes, the analysis will consider whether the data structure requires adjustment for clustering or institutional differences.
The results will be reported transparently, including coefficient estimates or other appropriate effect measures, standard errors, confidence intervals, p-values, and model-fit information. The interpretation will focus on the association between AI access and academic outcomes within the observed sample, avoiding unsupported claims that access itself causes improvements in performance.

5.8. Mediation Analysis: The Potential Role of AI Literacy

The eighth stage will investigate whether AI literacy statistically accounts for part of the relationship between access to AI-based learning enhancement technologies and academic outcomes.
The proposed mediation model considers AI access as the predictor, AI literacy as the mediator, and academic outcomes as the dependent variable. The model will examine whether access is associated with AI literacy and whether AI literacy is associated with academic outcomes after accounting for AI access.
The indirect association will be estimated using an appropriate mediation procedure. Where justified, bootstrap confidence intervals may be used to assess the uncertainty surrounding the estimated indirect effect. The analysis will also report the direct association between AI access and academic outcomes after accounting for the proposed mediator.
If the indirect effect is statistically distinguishable from zero under the prespecified analytical criteria, the findings may be consistent with the proposition that AI literacy helps explain part of the observed relationship between access and academic outcomes. If the evidence is inconclusive, the study will report that uncertainty rather than asserting that mediation has been established.
The analysis will also consider the limitations of the available design. Because the proposed study is cross-sectional, access, AI literacy, and academic outcomes are measured within the same general period. Consequently, the temporal ordering of these variables cannot be established conclusively. Students with stronger academic skills may be more likely to develop AI literacy or obtain access to particular resources, and unmeasured factors may influence multiple variables simultaneously.
For these reasons, the mediation analysis will be interpreted as an examination of a proposed statistical relationship rather than definitive evidence of a causal mechanism. Longitudinal research or appropriately designed intervention studies would be needed to investigate the temporal processes through which AI access and literacy may influence academic outcomes.

5.9. Evaluation of the Research Hypotheses

The final analytical stage will evaluate the evidence associated with the five research hypotheses. Each hypothesis will be assessed using the statistical procedure corresponding to its conceptual relationship and measurement strategy.
The first hypothesis concerns the association between socioeconomic conditions and AI access. Its evaluation will focus on whether the observed data indicate systematic differences in access across socioeconomic groups and on the magnitude and precision of those differences.
The second hypothesis concerns the relationship between AI access and academic outcomes. Its evaluation will consider the estimated association between the selected access measure and the defined academic outcome, including any relevant adjustment for measured covariates.
The third hypothesis addresses the relationship between AI literacy and effective AI use. The interpretation will depend on how effective use is operationalized. If the study measures only frequency of use, it will not be sufficient to conclude that students use AI effectively. The selected indicators must capture the relevant competencies or learning-oriented practices.
The fourth hypothesis concerns institutional support and equitable access to and use of AI technologies. Its evaluation will examine the associations between institutional support and the relevant access or use measures. If the study does not directly measure equity-related differences, conclusions should be limited to the measured relationships rather than generalized to overall educational equity.
The fifth hypothesis proposes that AI literacy statistically accounts for part of the relationship between AI access and academic outcomes. Its evaluation will depend on the estimated indirect effect and the uncertainty associated with that estimate. The results will be interpreted cautiously in view of the cross-sectional design.
For each hypothesis, the final report will state whether the evidence supports, does not support, or remains inconclusive regarding the proposed relationship. These conclusions will be based on the actual results and the analytical criteria established before examining the data.

5.10. Integrated Interpretation of the Results

The final synthesis will bring together the findings from the descriptive, comparative, correlational, and multivariable analyses to evaluate the proposed framework of AI-related academic inequality.
The synthesis will distinguish three related but separate dimensions: unequal access to AI technologies, unequal capacity to use those technologies effectively, and differences in academic outcomes. This distinction is essential because disparities in access do not necessarily produce equivalent disparities in learning, and differences in academic outcomes cannot automatically be attributed to AI use.
The analysis will examine whether the findings are consistent with the proposition that socioeconomic conditions shape technological opportunities, that AI literacy is associated with effective educational use, and that institutional support may help reduce barriers to participation. Where the evidence does not support a proposed relationship, the discussion will consider alternative explanations and the limitations of the measurement strategy.
Particular attention will be given to the difference between statistical associations and causal explanations. Even if students with greater AI access demonstrate different academic outcomes, the observed relationship may reflect a combination of technological resources, prior achievement, digital competence, institutional conditions, and other measured or unmeasured factors.
The results will therefore be interpreted in relation to the research questions, the conceptual framework, and the characteristics of the study population. Their implications for higher education policy and practice will be developed in the discussion section, with recommendations proportionate to the strength and limitations of the empirical evidence.
Ultimately, this analysis is intended to clarify how unequal access to AI-based learning enhancement technologies may be associated with academic inequality and to identify the conditions that warrant further investigation. The empirical conclusions will depend entirely on the data collected and the results of the statistical analyses.

6. Discussion

6.1. Unequal Access to Artificial Intelligence as an Emerging Dimension of Academic Inequality

The integration of artificial intelligence into higher education raises important questions concerning the distribution of educational opportunities. Although AI-based learning enhancement technologies can provide students with immediate feedback, personalized explanations, and additional academic support, their potential benefits depend on the conditions under which students access and use them. Consequently, the educational implications of AI cannot be understood solely in terms of technological innovation or adoption rates. They must also be examined in relation to the social, economic, and institutional conditions that shape students' opportunities to benefit from these technologies.
The digital inequality perspective provides a useful framework for understanding this issue. Traditional discussions of the digital divide have emphasized differences in access to technological infrastructure, digital competencies, and the benefits obtained from technology use. The expansion of AI-supported education introduces additional considerations because effective use may require students to understand how AI systems operate, formulate appropriate prompts, evaluate generated information, and integrate AI outputs into their learning processes.
These considerations suggest that academic inequality in AI-supported environments may involve several interconnected dimensions. Students may differ in their ability to obtain suitable devices, maintain reliable internet connectivity, access advanced AI features, and develop the competencies necessary for responsible use. Differences in these conditions may create unequal opportunities to obtain educational assistance, even when AI technologies are widely available.
An important distinction is therefore necessary between the availability of AI technologies and the equitable distribution of their educational benefits. The presence of AI applications within a university or educational system does not necessarily imply that all students can use them under comparable conditions. Meaningful access requires not only technological availability but also affordability, accessibility, appropriate competencies, and sufficient opportunities to integrate these resources into academic activities.
From this perspective, AI may represent an additional dimension of digital inequality rather than an independent source of academic disadvantage. Its relationship with educational inequality will depend on how technological resources interact with existing socioeconomic differences, institutional practices, and students' individual learning conditions. Empirical research is required to determine the extent to which these relationships occur in specific higher education contexts.

6.2. Socioeconomic Conditions and the Unequal Distribution of AI Opportunities

Socioeconomic conditions may influence students' opportunities to access and use AI-based learning enhancement technologies. Students with greater financial resources may have more opportunities to obtain suitable devices, maintain reliable internet connections, purchase subscriptions, and participate in supplementary digital training. Students experiencing financial constraints may face additional barriers when these resources require ongoing expenditure or depend on infrastructure that is not consistently available.
These differences are particularly relevant when AI-supported activities become integrated into academic assignments, independent study, research projects, and assessment preparation. If students are expected to use AI technologies without receiving equivalent access to the necessary resources, existing differences in educational opportunities may

become more pronounced.

However, the relationship between socioeconomic status and AI access should not be interpreted as uniform or inevitable. Publicly available applications, institutional subscriptions, library services, peer support, and targeted training programs may reduce some of the barriers associated with limited financial resources. Conversely, students with greater financial resources may still experience difficulties using AI effectively if they lack the necessary competencies or receive insufficient academic guidance.

The relevant question is therefore not simply whether socioeconomic differences exist, but how financial circumstances interact with technological access and educational support. Examining these relationships may help identify which barriers are most consequential and which interventions are most likely to improve access.

For higher education institutions, this perspective highlights the importance of evaluating the distribution of AI-related resources before assuming that technology adoption benefits all students equally. Equitable implementation may require accessible institutional tools, reliable campus infrastructure, training opportunities, and alternatives for students who cannot afford commercial services.

Nevertheless, the effectiveness of these interventions should be established through evaluation rather than assumed. Research should investigate whether specific institutional initiatives are associated with measurable reductions in access disparities and improvements in students' educational opportunities.

6.3. AI Literacy and Differences in the Effective Use of Learning Technologies

Access to AI technologies represents only one component of students' opportunities to benefit from AI-supported learning. Students must also develop the competencies necessary to interact with these systems, assess their outputs, and use the information they provide appropriately.

AI literacy is therefore an important dimension of the proposed relationship between technological access and academic inequality. Students with stronger AI-related competencies may be better positioned to formulate precise questions, identify incomplete explanations, compare generated information with reliable sources, and integrate AI assistance into independent learning activities. Students with limited competencies may have greater difficulty recognizing errors, evaluating uncertainty, or determining whether generated content meets academic requirements.

These differences suggest that equal access to the same AI application may not produce equivalent educational experiences. A student who can critically evaluate AI-generated information may use the technology to strengthen understanding, whereas another student may accept inaccurate information or rely on generated responses without sufficiently engaging with the underlying concepts.

At the same time, AI literacy should not be reduced to technical proficiency. Effective use also involves critical thinking, information evaluation, ethical awareness, and an understanding of the limitations of automated systems. Students need to recognize that AI-generated content may contain factual inaccuracies, reflect biases, or omit important contextual information.

Educational institutions can address these challenges by incorporating AI literacy into teaching and learning activities. Training may include prompt formulation, verification of information, responsible citation practices, recognition of bias, and the appropriate integration of AI into academic work. Such initiatives should be evaluated according to whether they improve students' competencies and support meaningful learning rather than simply increasing the frequency of AI use.

The proposed framework consequently treats AI literacy as a potential explanatory factor in the relationship between access and academic outcomes. Whether literacy statistically accounts for part of this relationship remains an empirical question that must be investigated using appropriately defined measures and data.

6.4. Institutional Support as a Potential Mechanism for Reducing Inequality

Higher education institutions influence the conditions under which AI technologies are introduced, accessed, and used. Institutional decisions concerning infrastructure, training, accessibility, licensing, academic integrity, and technological support may affect students' opportunities to benefit from AI-supported learning.

A university that provides accessible AI resources and structured guidance may reduce some barriers associated with students' financial circumstances and previous technological experience. Institutional support may also help establish consistent expectations concerning responsible use, the verification of generated information, and the role of AI in independent learning.

Conversely, institutions that encourage AI adoption without providing adequate guidance or considering differences in students' resources may unintentionally create unequal conditions. Students who already possess advanced digital competencies and access to paid services may be better prepared to respond to these expectations, while others may struggle to meet them.

Institutional support should therefore be understood as more than the provision of technological tools. It includes the policies, pedagogical practices, training opportunities, and support systems that help students use AI effectively and responsibly.

Several strategies may be relevant. Institutions could provide access to approved AI tools through libraries or learning platforms, offer training adapted to different levels of prior knowledge, develop clear academic integrity guidelines, and ensure that essential learning activities do not depend on students purchasing services they cannot afford. They could also provide alternative ways to complete academic tasks when students encounter technological or accessibility barriers.

However, the effectiveness of these strategies depends on their design and implementation. Providing an AI application does not automatically ensure that students will use it effectively, and training opportunities may have limited effects if students cannot access the required infrastructure. Institutional interventions should therefore be evaluated as coordinated measures rather than isolated technological initiatives.

Future empirical studies should examine whether differences in institutional support are associated with differences in AI access, AI literacy, and academic outcomes. Such evidence could help universities identify which policies are most effective in promoting equitable participation in AI-supported learning.

6.5. The Relationship Between AI Access and Academic Outcomes

The relationship between access to AI-based learning enhancement technologies and academic outcomes is a central component of the proposed research framework. AI technologies may offer educational advantages by providing immediate explanations, supporting independent study, facilitating information organization, and helping students practice unfamiliar concepts. These capabilities may be particularly useful when conventional academic support is limited or unavailable.

Nevertheless, the availability of AI does not guarantee improved academic performance. The educational value of these tools may depend on students' prior knowledge, learning strategies, AI literacy, the quality of the generated information, and the extent to which AI use complements rather than replaces independent reasoning.

For example, using AI to request alternative explanations of a difficult concept may help a student identify misunderstandings and strengthen comprehension. By contrast, relying exclusively on generated answers without evaluating their accuracy may produce an incomplete understanding of the subject. The same technology can therefore be incorporated into different learning practices with potentially different educational implications.

These considerations indicate that the relationship between AI access and academic outcomes should not be interpreted as a simple direct association. Research should distinguish between access to AI, patterns of use, the competencies required for effective use, and the academic outcomes being measured.

It is also important to account for prior academic achievement and other relevant characteristics when examining this relationship. Students with stronger academic preparation may be more likely to use AI effectively, while differences in institutional resources and socioeconomic circumstances may influence both technology access and academic performance. Without appropriate consideration of these factors, an observed association may be misinterpreted.

The proposed study seeks to address these concerns by examining AI access alongside AI literacy, socioeconomic conditions, and institutional support. The resulting analysis may clarify whether AI access is associated with academic outcomes within the study population and whether that relationship changes when relevant characteristics are considered.

Because the proposed research design is observational and cross-sectional, however, any identified association should be interpreted cautiously. The findings would not, by themselves, establish that access to AI causes improvements or declines in academic performance.

6.6. Reconsidering Academic Inequality in AI-Supported Higher Education

Academic inequality in AI-supported higher education should be examined as a multidimensional phenomenon involving differences in technological resources, competencies, institutional opportunities, and educational outcomes.

A narrow approach that measures only whether students use AI may overlook important differences in the conditions under which that use occurs. Two students may report using the same application while differing substantially in connectivity, access to advanced features, ability to evaluate generated information, and opportunities to receive institutional support.

Similarly, differences in academic performance cannot automatically be attributed to disparities in AI access. Academic outcomes are influenced by multiple factors, including prior educational experiences, teaching quality, motivation, financial circumstances, time available for study, and access to conventional academic support.

A comprehensive approach should therefore distinguish between at least three dimensions of inequality. The first is inequality in technological access, which concerns the availability and affordability of AI resources. The second is inequality in effective use, which concerns students' competencies and opportunities to incorporate AI into meaningful learning activities. The third is inequality in educational outcomes, which concerns differences in academic performance or other clearly defined indicators of educational achievement.

These dimensions may be related, but they are not interchangeable. A difference in access does not necessarily establish a difference in effective use, and a difference in effective use does not necessarily demonstrate a corresponding difference in academic performance.

This distinction has practical implications for research and educational policy. Universities seeking to reduce AI-related inequality should evaluate not only how many students have access to AI tools but also whether those students can use the tools effectively and whether educational opportunities are distributed equitably across different groups.

The proposed conceptual framework offers a basis for examining these dimensions together. Its empirical value will depend on the quality of the measures, the characteristics of the study population, and the strength of the evidence obtained through the planned analyses.

6.7. Theoretical Implications

The study contributes conceptually to discussions of digital inequality by examining AI access in relation to both the resources required for participation and the competencies necessary for effective educational use.

The digital inequality perspective suggests that disparities in technology-related outcomes cannot be explained solely by the presence or absence of technological infrastructure. Individuals may differ in their skills, patterns of use, and ability to convert technological resources into meaningful benefits. AI-supported education provides an important context in which these distinctions can be examined.

The proposed framework extends this perspective by considering AI literacy and institutional support alongside socioeconomic conditions and technological access. AI literacy represents the competencies needed to interact critically with AI systems, while institutional support represents the educational conditions that may facilitate or constrain the development and application of those competencies.

This integrated perspective may help researchers investigate whether disparities in access are associated with disparities in effective use and whether these differences correspond to variations in academic outcomes. It also emphasizes the importance of distinguishing between the availability of technology and the educational benefits obtained from its use.

The framework should not be interpreted as establishing a new causal theory or demonstrating that AI necessarily increases academic inequality. Rather, it provides a structure for investigating the conditions under which AI-supported learning may reproduce, reduce, or reshape existing differences in educational opportunity.

Its theoretical contribution will depend on the extent to which subsequent empirical analysis supports the proposed relationships and clarifies the conditions under which those relationships vary across student groups and institutional contexts.

6.8. Practical Implications for Higher Education Institutions

The proposed framework has several potential implications for university leaders, educators, technology coordinators, and educational policymakers.

First, institutions should assess disparities in students' access to AI technologies before introducing AI-dependent learning activities. Such assessments may identify barriers associated with device availability, connectivity, subscription costs, accessibility requirements, and limited institutional provision.

Second, universities should develop AI literacy initiatives that address both technical and critical competencies. Students need opportunities to learn how to formulate effective prompts, verify generated information, recognize limitations, and integrate AI assistance into independent academic work.

Third, institutions should establish clear and accessible guidelines for responsible AI use. Guidance should explain acceptable applications, expectations concerning disclosure where required, verification of information, and the preservation of academic integrity. Clear policies may reduce uncertainty and help students use AI in ways that support rather than undermine learning.

Fourth, universities should consider the equity implications of requiring or strongly encouraging students to use commercial AI services. Where such tools are necessary for essential learning activities, institutions should examine whether equitable access can be provided or whether suitable alternatives are available.

Fifth, institutions should monitor the effects of their AI-related policies. Evaluations could examine participation in training, access to institutional tools, changes in AI literacy, student experiences, and relevant educational outcomes. Where possible, these evaluations should compare outcomes across groups to identify whether inequalities are narrowing or persisting.

Finally, AI-related educational policies should be reviewed as technologies and student needs evolve. A strategy that addresses current access barriers may become insufficient as new applications, pricing arrangements, and educational practices emerge.

These recommendations represent potential applications of the conceptual framework rather than interventions whose effectiveness has already been demonstrated by the present study. Their implementation should be accompanied by systematic evaluation.

6.9. Limitations and Directions for Future Research

Several limitations should be considered when interpreting the proposed framework and the evidence that may emerge from its application.

First, a cross-sectional design can identify associations among AI access, AI literacy, institutional support, and academic outcomes, but it cannot establish temporal ordering or definitive causal relationships. Longitudinal research would help clarify how students' access and competencies evolve over time and whether changes in these conditions precede changes in academic outcomes.

Second, self-reported measures may introduce measurement error. Students may overestimate or underestimate their AI literacy, report their technology use inaccurately, or interpret questionnaire items differently. Future studies could combine self-reported measures with objective assessments of AI literacy, documented access indicators, and authorized academic records.

Third, the multidimensional nature of academic inequality creates challenges for measurement. A single indicator, such as course grades, may not capture differences in learning opportunities, academic participation, or the ability to obtain educational support. Future research should consider multiple clearly defined indicators where the research design and available data permit.

Fourth, the characteristics of the study population may limit the generalizability of the findings. Relationships observed among students from a particular country, institution, or academic discipline may not apply equally to other educational settings. Comparative studies across institutions and countries could help establish the extent to which these relationships vary across contexts.

Fifth, the rapid evolution of AI technologies may affect the relevance of particular access measures over time. Differences in subscription models, available features, institutional policies, and student familiarity may change as technologies develop. Repeated assessments may therefore be necessary to capture changes in the conditions of AI-supported learning.

Future research should also examine the effectiveness of specific interventions designed to reduce AI-related inequalities. Evaluations of institutional access programs, AI literacy training, and inclusive digital learning policies could provide evidence about which approaches are associated with improvements in students' opportunities to benefit from AI. Where feasible, longitudinal or quasi-experimental designs could provide stronger evidence about changes over time and the potential effects of particular interventions. Qualitative interviews and focus groups could complement quantitative analyses by explaining how students experience access barriers, make decisions about AI use, and perceive the support available from their institutions.

These approaches would help move the research agenda beyond identifying potential inequalities toward understanding their mechanisms and evaluating practical strategies for addressing them.

6.10. Overall Interpretation

The central argument developed in this discussion is that the relationship between artificial intelligence and academic inequality should be examined through the conditions that shape students' opportunities to access, understand, and use AI-based learning enhancement technologies.

AI offers possibilities for expanding educational support, but its availability alone does not guarantee equitable participation or equivalent learning benefits. Differences in financial resources, technological infrastructure, AI literacy, and institutional support may influence how students encounter and incorporate AI into their academic activities.

A comprehensive analysis should therefore distinguish between unequal access, unequal effective use, and unequal academic outcomes. It should also consider the broader educational context in which these dimensions interact, recognizing that academic performance is influenced by multiple factors beyond technology access.

The proposed framework brings these dimensions together to support empirical investigation of AI-related academic inequality. Its purpose is not to assume that AI inevitably increases educational disparities, but to identify the conditions under which unequal access may be associated with unequal academic opportunities.

Ultimately, a more equitable integration of AI into higher education requires attention to both technological innovation and the distribution of the resources and competencies necessary to benefit from it. Empirical evidence concerning these relationships can help institutions develop more inclusive policies, evaluate the consequences of AI adoption, and ensure that technological advancement is accompanied by meaningful opportunities for diverse student populations.

7. Conclusion

Artificial intelligence is becoming an increasingly influential component of higher education, creating new opportunities to improve learning, support academic work, and expand access to educational resources. However, the educational benefits associated with these technologies are not necessarily distributed equally among university students. Differences in access to digital infrastructure, socioeconomic resources, AI literacy, and institutional support may influence students' capacity to use artificial intelligence effectively. Consequently, the growing integration of AI into higher education raises an important question concerning educational equity: whether these technologies will reduce existing academic inequalities or reinforce disparities between students with different levels of access and support.

This article examines the relationship between unequal access to AI-based learning enhancement technologies and academic inequality in higher education. Its central argument is that access to artificial intelligence should not be understood exclusively as the possession of a technological device, an internet connection, or permission to use a particular application. Rather, meaningful access involves a combination of material resources, opportunities to develop AI literacy, institutional guidance, and the ability to integrate these technologies into learning activities in academically productive and responsible ways. From this perspective, unequal access represents a multidimensional phenomenon that may influence students' educational experiences and their opportunities to benefit from emerging technologies.

The proposed analytical framework emphasizes the interaction between socioeconomic conditions, AI access, AI literacy, institutional support, and academic outcomes. Socioeconomic conditions may influence the resources available to students, including access to reliable devices, stable connectivity, and advanced AI tools. AI literacy may affect their ability to formulate effective prompts, assess the accuracy of generated information, identify potential biases, and use AI outputs critically. Institutional support may further shape these experiences by determining whether students receive appropriate training, guidance, and equitable opportunities to use AI technologies. Considered together, these dimensions provide a foundation for examining why students who attend the same university may experience substantially different educational benefits from artificial intelligence.

A central implication of this framework is that the expansion of AI technologies does not automatically produce greater educational equality. Although AI applications may provide personalized explanations, immediate feedback, writing assistance, and additional learning opportunities, their benefits depend on the conditions under which students access and use them. Students with greater technological resources, stronger digital competencies, and more effective institutional support may be better positioned to incorporate AI into their academic activities. Conversely, students who experience limited connectivity, restricted access to advanced tools, insufficient training, or uncertainty about responsible use may face additional barriers. These possibilities highlight the importance of examining not only whether students use AI but also how, why, and under what circumstances they use it.

The distinction between access and effective use is particularly important for understanding academic inequality. Equal access to a particular AI application does not necessarily mean that all students possess equivalent opportunities to benefit from it. Differences in critical thinking, disciplinary knowledge, technological confidence, and the ability to evaluate generated content may influence the quality of AI-supported learning. Therefore, initiatives designed to improve educational equity should address both technological availability and the development of students' capacities to use these tools effectively. Such efforts are essential to ensuring that the educational transformation associated with AI does not deepen existing inequalities and instead supports a more equitable, accessible, and academically responsible learning environment.

Institutional responsibility is consequently a key consideration. Universities have opportunities to establish policies and educational practices that promote equitable access to AI-based learning enhancement technologies. These actions may include providing accessible AI tools, strengthening digital infrastructure, offering AI literacy programs, developing transparent guidelines for responsible use, and supporting faculty members in integrating AI into teaching. Institutions may also benefit from assessing whether their AI policies unintentionally disadvantage students who have fewer resources or less prior experience with emerging technologies. A comprehensive approach should consider accessibility, privacy, academic integrity, algorithmic bias, transparency, and the diverse circumstances of the student population.

The article also highlights the importance of evaluating AI-related educational inequalities through multiple dimensions of academic experience. Academic outcomes should not be reduced to grades alone. Depending on the research context and the availability of reliable measures, relevant outcomes may include learning engagement, perceived academic competence, quality of academic work, access to learning support, and students' confidence in completing academic tasks. Examining several dimensions may provide a more comprehensive understanding of whether AI technologies contribute to meaningful learning opportunities or primarily benefit students who already possess educational advantages. However, these dimensions must be operationalized carefully and evaluated using appropriate research instruments.

From a research perspective, the proposed framework offers a basis for empirical investigation into the mechanisms connecting AI access and academic inequality. Future studies should examine differences in access across socioeconomic groups, evaluate students' AI literacy, and investigate the relationship between institutional support and the effective use of AI. Quantitative analyses may identify associations among these variables, while qualitative interviews may help explain students' experiences, concerns, and strategies for navigating unequal access. Longitudinal research would be particularly valuable for determining whether disparities change as AI technologies become more widely available and universities introduce new policies or training programs.

Nevertheless, the conclusions that can be drawn from this article must be interpreted in light of its current evidentiary limitations. The proposed framework and hypotheses require empirical testing before any definitive claims can be made about the strength, direction, or statistical significance of the relationships discussed. In particular, cross-sectional associations would not independently establish causality, and the relationship between AI access and academic performance may be influenced by additional factors, including prior academic achievement, field of study, teaching practices, motivation, and institutional characteristics. Future research should therefore employ transparent sampling procedures, validated measures, appropriate statistical analyses, and clearly documented ethical safeguards.

Ultimately, promoting equity in AI-supported higher education requires a shift from technological adoption alone toward an approach centered on students' capabilities, institutional responsibility, and meaningful educational opportunities. The relevant question is not simply whether artificial intelligence is available to university students, but whether students with different socioeconomic circumstances have fair opportunities to access, understand, evaluate, and benefit from these technologies. By examining the interaction between technological resources, AI literacy, institutional support, and academic outcomes, future empirical research can help universities develop more inclusive strategies for integrating artificial intelligence into higher education. Such efforts are essential to ensuring that the educational transformation associated with AI does not deepen existing inequalities and instead supports a more equitable, accessible, and academically responsible learning environment.

Data Availability Statement

No empirical dataset was generated or analyzed for the present manuscript at the current stage of development. The article presents a conceptual analysis and a proposed research framework for examining the relationship between unequal access to artificial intelligence (AI)- based learning enhancement technologies and academic inequality in higher education. Consequently, there are no original research data available for public deposit or sharing. If the proposed empirical study is subsequently conducted, the data availability statement will be revised to specify the location of the dataset, the applicable access conditions, and any restrictions necessary to protect participant confidentiality.

Ethics Statement

This manuscript, in its current conceptual form, does not report original research involving human participants, identifiable personal information, or human biological materials. Therefore, no participant recruitment, intervention, or collection of primary human-subject data is reported in this version of the manuscript.

Any subsequent empirical investigation involving university students or other human participants should be conducted in accordance with applicable institutional requirements and ethical principles for research involving human participants. Where required, approval must be obtained from the appropriate institutional research ethics committee before data collection begins. Informed consent, voluntary participation, confidentiality, secure data management, and the protection of participants' rights must be ensured throughout the research process.

Author Contributions

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Conflict of Interest

The authors should disclose any financial or non-financial relationships that could reasonably be perceived as influencing the research, its interpretation, or its publication. A final declaration of competing interests must be confirmed by all authors before submission. If all authors confirm that no relevant competing interests exist, the following statement may be used: "The authors declare no competing interests."

Generative AI Statement

During the preparation of this manuscript, ChatGPT, an AI-based language model developed by OpenAI, was used to assist with drafting, organizing, and refining portions of the text. The tool was used as a writing aid and not as a substitute for scholarly judgment, independent verification, or author responsibility.

The authors are responsible for reviewing and verifying the accuracy of the manuscript, checking the validity and relevance of the cited references, ensuring that the final text reflects their own scholarly assessment, and complying with the target journal's policies regarding generative AI. ChatGPT is not listed as an author and does not bear responsibility for the final published work.

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