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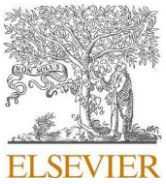

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Research paper

Artificial Intelligence Reshapes Academic Inequality in Higher Education Through Unequal Access to Learning Enhancement Technologies

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ABSTRACT

Introduction: Artificial intelligence (AI) is transforming higher education by expanding access to personalized learning, automated feedback, intelligent tutoring, and academic assistance. However, unequal access to AI-enhanced learning technologies may create differences in students' opportunities to benefit from these innovations, potentially reinforcing existing academic inequalities. This study aims to examine the relationship between unequal access to AI-enhanced learning technologies and academic inequality among university students, considering the roles of socioeconomic status, AI literacy, and institutional support.

Methodology: The study will employ a quantitative approach with a correlational and explanatory orientation and a non-experimental, cross-sectional design. Data will be collected through a structured questionnaire administered to university students. The proposed analytical framework will assess socioeconomic status, access to AI-enhanced learning technologies, AI literacy, institutional support, learning engagement, and self-reported academic outcomes. Statistical analyses will include descriptive statistics, correlation analysis, and multivariate regression. Structural equation modeling may be employed if the sample size, measurement properties, and model specification support its use. The validity and reliability of the measurement instruments will be evaluated using appropriate statistical procedures. The final sample size, participant characteristics, measurement instruments, and analytical procedures will be reported after the empirical study has been conducted.

Results: The empirical results will establish the extent to which socioeconomic status is associated with access to AI-enhanced learning technologies and whether AI literacy and institutional support are associated with differences in students' educational use of these tools. The analysis will also examine the relationships between technological access, learning engagement, and self-reported academic outcomes. Regression coefficients, confidence intervals, effect sizes, and statistical significance will be reported based on the observed data. No empirical findings are asserted at this stage because data collection and statistical analysis have not yet been completed.

Conclusion: This study seeks to advance understanding of academic inequality in AI-mediated higher education by distinguishing access to technological resources from students' capacity to use them effectively for learning. Its proposed framework emphasizes the potential importance of socioeconomic resources, AI literacy, and institutional support in shaping educational opportunities. The findings, once established empirically, may inform university policies aimed at promoting equitable access to AI-enhanced learning technologies and developing students' competencies for their responsible and effective use.

1. Introduction

Artificial intelligence (AI), particularly generative artificial intelligence (GenAI), is transforming higher education by expanding the possibilities for personalized learning, academic writing, information retrieval, feedback generation, and problem-solving. Tools based on large language models can provide students with immediate explanations, support the organization of ideas, and facilitate access to learning resources. However, the educational benefits of these technologies should not be assumed to be equally distributed. Students differ in their access to technological infrastructure, their ability to evaluate AI-generated information, their financial capacity to use advanced tools, and the institutional support available to guide their academic practices. Consequently, the integration of AI into higher education raises an important question: can technologies designed to expand learning opportunities also reproduce or intensify existing academic inequalities?

Research on the digital divide has traditionally distinguished between inequalities in access to technology, differences in digital skills and patterns of use, and disparities in the outcomes individuals obtain from technological engagement. The emergence of GenAI adds a new dimension to this discussion because access alone may not determine whether students can use these tools effectively for academic purposes. The ability to formulate appropriate prompts, evaluate generated responses, recognize inaccuracies, and integrate AI-supported information into disciplinary learning may be as important as having a device or an internet connection. From this perspective, AI-related inequality should be examined not only as a problem of technological availability but also as a question of capabilities, educational opportunities, and the distribution of academic advantages.

Recent empirical research provides initial support for this concern. Zhang et al. (2026) examined college students' digital literacy, AI literacy, and ChatGPT activities from a digital divide perspective. Their findings indicated that socioeconomic status was more strongly associated with AI literacy than with general digital literacy, while different forms of ChatGPT use were associated with different academic outcomes. Similarly, Beckman et al. (2025), in a mixed-methods study involving 194 university students, identified different profiles of GenAI knowledge, literacy, and intended academic use. Their findings highlighted the possibility that differences in students' capabilities and patterns of engagement may reflect existing digital inequalities. Together, these studies suggest that the educational implications of AI depend on more than the mere presence of the technology.

Nevertheless, the relationship between AI access and academic inequality remains complex. Access to AI-enhanced learning technologies may be influenced by students' socioeconomic circumstances, the quality of their internet connection, the devices available to them, and whether they can afford subscription-based services. At the same time, institutional conditions may shape students' opportunities to develop AI literacy and use these technologies in academically meaningful ways. Universities differ in their technological infrastructure, guidance on responsible AI use, availability of training, and integration of AI into teaching and assessment. These differences may create unequal conditions even among students enrolled in the same higher education system.

A further concern is that unequal access may interact with unequal capabilities. Students who have reliable access to advanced AI tools and receive appropriate guidance may be better positioned to use them for feedback, research assistance, language support, and the clarification of complex concepts. Conversely, students with limited access or insufficient AI literacy may be less able to evaluate the quality of generated information or identify situations in which AI assistance is inappropriate. These differences could contribute to unequal learning experiences and perceived academic outcomes. However, such consequences should be investigated empirically rather than treated as inevitable: the educational effects of AI may vary according to how students use the technology, the tasks they undertake, and the support provided by their institutions.

International policy discussions have also emphasized the importance of equitable and human-centred approaches to AI in education. UNESCO's guidance on generative AI highlights the need to address ethical, regulatory, pedagogical, and capacity-building challenges while ensuring that the use of these technologies remains safe, meaningful, and inclusive (Miao & Holmes, 2023). This perspective indicates that the implementation of AI in higher education should not be evaluated exclusively in terms of innovation or efficiency. It should also be assessed in relation to students' ability to access, understand, critically evaluate, and benefit from these tools under fair educational conditions.

Despite the growing scholarly attention to GenAI in higher education, further research is needed to understand how socioeconomic circumstances, access to AI-enhanced learning technologies, AI literacy, and institutional support jointly relate to academic inequality. Existing studies provide valuable evidence concerning students' AI literacy and use patterns, but the relationships among access conditions, capabilities, institutional support, and self-reported academic outcomes require continued examination across different educational contexts. A particular challenge is to distinguish the availability of AI tools from students' actual capacity to use them effectively and from the academic advantages they perceive or experience as a result.

This issue is particularly relevant in higher education contexts where students may experience substantial differences in technological resources and institutional support. Examining these relationships can help universities identify whether AI-related opportunities are distributed equitably and which factors may be associated with unequal academic experiences. Such an approach also avoids technological determinism: AI does not necessarily reduce or increase inequality by itself. Its consequences may depend on the social, economic, educational, and institutional conditions under which it is introduced and used.

Against this background, the present article examines how unequal access to AI-enhanced learning technologies may be associated with academic inequality in higher education. It focuses on five interrelated dimensions: socioeconomic conditions, access to AI-enhanced learning technologies, AI literacy, institutional support, and self-reported academic outcomes. By considering these dimensions together, the study aims to move beyond a narrow understanding of the digital divide as a simple difference in technology ownership or availability.

The study is guided by the following research questions:

1. To what extent do students from different socioeconomic backgrounds report unequal access to AI-enhanced learning technologies?
2. How is access to AI-enhanced learning technologies associated with students' AI literacy?
3. What relationship exists between AI literacy and students' self-reported academic outcomes?
4. Does institutional support relate to differences in students' access to and use of AI-enhanced learning technologies?
5. To what extent are socioeconomic conditions, access to AI-enhanced learning technologies, AI literacy, and institutional support associated with academic inequality in higher education?

Accordingly, the article seeks to contribute to the literature on digital inequality and educational technology by conceptualizing AI-related academic inequality as a multidimensional phenomenon involving access, capabilities, institutional conditions, and potential educational outcomes. Its practical relevance lies in informing institutional strategies that combine equitable access to AI tools with AI literacy development, transparent guidance, and appropriate educational support. Ultimately, the central concern is not simply whether university students use AI, but whether they have fair opportunities to use it critically, responsibly, and productively in support of their learning.

2. Literature Review And Theoretical Framework

2.1. Academic inequality in higher education

Academic inequality refers to differences in students' educational opportunities, learning conditions, academic experiences, and outcomes that are associated with unequal access to economic, technological, social, and institutional resources. Although universities may formally provide students with the same curriculum and academic expectations, students do not necessarily possess equivalent resources to meet these expectations. Differences in financial circumstances, educational backgrounds, digital competencies, and access to academic support can shape how students engage with learning activities and benefit from available educational opportunities.

The expansion of digital technologies has added new dimensions to these inequalities. Students may have access to the same online learning platform but differ in the quality of their devices, internet connectivity, technological skills, and ability to use digital resources to address academic challenges. Consequently, equal availability of educational technologies does not necessarily guarantee equal opportunities to benefit from them.

The emergence of generative artificial intelligence introduces an additional dimension to this issue. AI tools can support academic activities by providing explanations, generating examples, organizing information, and facilitating the development of ideas. However, the educational value of these applications may depend on students' ability to access and use them effectively. Zhang et al. (2026) examined the relationships among socioeconomic status, digital and AI literacy, ChatGPT activities, and perceived educational outcomes. Their findings illustrate that AI-related educational experiences are associated with several dimensions of digital inequality and that the consequences of AI use may vary according to the type of academic activity performed.

Academic inequality in the context of AI should therefore be understood as a multidimensional phenomenon. It may involve unequal technological access, differences in AI-related capabilities, variation in institutional support, and disparities in students' perceived ability to benefit from AI-assisted learning. This conceptualization provides a basis for examining how these dimensions are associated with educational experiences in higher education.

2.2. The Digital Divide and Unequal Access to AI Technologies

The digital divide provides a theoretical foundation for understanding how inequalities in technological access and use may contribute to broader social and educational disparities. Rather than representing a single difference between individuals who have technology and those who do not, the digital divide encompasses several interrelated dimensions, including access to technological resources, digital skills, patterns of use, and the outcomes associated with technology engagement.

In higher education, access to AI-enhanced learning technologies can include the availability of appropriate devices, reliable internet connectivity, access to AI applications, and the opportunity to use advanced features when needed. Students may encounter different constraints depending on their socioeconomic circumstances. For example, the cost of devices, connectivity, or paid AI subscriptions may limit some students' access to particular tools. Others may rely on shared devices, restricted internet plans, or applications that offer fewer capabilities.

However, access should not be treated as a purely financial or technical issue. The ability to use AI tools in academic settings also depends on whether students know which applications are appropriate for particular tasks, understand their limitations, and can integrate their outputs into their learning processes. Thus, two students with access to the same AI application may experience different educational opportunities because they possess different levels of knowledge, confidence, and support.

Beckman et al. (2025) explored variations in university students' knowledge, AI literacy, and intended use of generative AI. Their study identified different profiles of students, illustrating that familiarity with and intended engagement in AI-supported academic activities are not uniform. The authors also highlighted the importance of considering access, capabilities, and institutional support when examining the potential emergence of a generative AI divide.

These findings suggest that research on AI-related inequality should distinguish between access to technology and the capacity to benefit from it. Accordingly, the present study conceptualizes access to AI-enhanced learning technologies as a relevant explanatory dimension of academic inequality rather than assuming that access alone determines academic success.

2.3. AI Literacy as a Mechanism of Educational Differentiation

AI literacy refers broadly to the knowledge, skills, and critical understanding required to interact with artificial intelligence systems appropriately and effectively. In higher education, this may include understanding how AI applications generate responses, formulating suitable prompts, evaluating the reliability of generated information, identifying possible errors or biases, protecting personal information, and applying AI tools in accordance with academic and ethical expectations.

AI literacy is particularly relevant because generative AI systems can produce fluent and persuasive responses that are not necessarily accurate, complete, or appropriate for a specific academic task. Students who cannot evaluate these outputs may accept unsupported information or rely excessively on automated assistance. In contrast, students who can critically assess AI-generated content may be better positioned to use these tools as supplementary learning resources.

Zhang et al. (2026) found that AI literacy was associated with students' engagement in different types of ChatGPT activities. Their analysis distinguished between activities that supported academic work and activities that displaced academic effort. The distinction is important because the frequency of AI use does not, by itself, indicate whether students are using the technology in ways that support learning. AI-assisted activities may complement students' academic efforts, but they may also replace processes through which students develop their own understanding and skills.

Beckman et al. (2025) likewise identified differences in AI knowledge and intended academic use among university students. Their findings support the need to consider AI literacy when investigating how students approach generative AI in higher education.

From an inequality perspective, differences in AI literacy may create unequal opportunities to benefit from the same technological resources. Students with stronger AI-related competencies may be more capable of evaluating responses, adapting outputs to disciplinary requirements, and using AI to support learning. Students with limited AI literacy may experience greater uncertainty or struggle to distinguish useful assistance from misleading information.

Nevertheless, AI literacy should not be assumed to eliminate the consequences of socioeconomic inequality. Students may possess strong critical skills while still facing limited connectivity, restricted access to advanced tools, or inadequate institutional support. For this reason, the present study considers AI literacy alongside technological access and institutional support rather than treating it as an isolated determinant of academic outcomes.

2.4. Institutional Support and Equitable AI Integration

Institutional support refers to the resources, guidance, training, policies, and educational opportunities provided by universities to help students use AI technologies responsibly and effectively. It may include AI literacy workshops, access to approved applications, clear academic integrity policies, guidance on verifying AI-generated information, and opportunities to discuss the appropriate use of AI with instructors.

Institutional support is important because students may have unequal opportunities to develop AI-related competencies outside the university. Some students may receive guidance from peers, family members, or external educational resources, whereas others may depend primarily on the learning opportunities offered by their institutions. Universities can therefore influence the conditions under which students acquire the knowledge required to use AI effectively.

UNESCO's guidance on generative AI in education and research emphasizes the importance of a human-centred approach, appropriate safeguards, capacity development, and the responsible integration of these technologies into educational settings (Miao & Holmes, 2023). These principles suggest that institutional AI strategies should address not only technological innovation but also equity, educational quality, and students' capacity to engage critically with AI systems.

Institutional support may be particularly important when access to technology is uneven. Providing training without ensuring that students can access suitable tools may limit the practical value of that training. Conversely, providing AI applications without guidance may leave students uncertain about their appropriate use or unable to evaluate their outputs. An equitable institutional strategy should therefore consider the relationship between access, capability development, and pedagogical guidance.

For the purposes of this study, institutional support is conceptualized as a contextual factor that may be associated with students' access to AI-enhanced learning technologies, their AI literacy, and their self-reported academic outcomes. Its role will need to be examined empirically rather than assumed in advance.

2.5. AI-Enhanced Learning Technologies and Self-Reported Academic Outcomes

AI-enhanced learning technologies are digital applications that incorporate AI capabilities to support activities such as explaining concepts, providing feedback, generating examples, assisting with writing, summarizing information, and facilitating problem-solving. In higher education, these applications may supplement conventional teaching and learning practices by offering students additional opportunities to engage with academic content.

However, their potential value depends on how they are used. AI may help students clarify unfamiliar concepts, organize study activities, and receive preliminary feedback. At the same time, uncritical dependence on AI-generated responses may reduce students' engagement with the underlying academic task or encourage the acceptance of inaccurate information.

Zhang et al. (2026) found that different types of ChatGPT activities were associated with different perceived educational outcomes. Their findings distinguish academic-support activities from academic-displacement activities, highlighting the importance of examining the nature of AI use rather than measuring use frequency alone.

In the present study, self-reported academic outcomes refer to students' perceptions of how AI-enhanced learning technologies relate to their academic learning experiences. These perceptions may include perceived understanding of course content, confidence in completing academic tasks, perceived productivity, and the perceived usefulness of AI-supported learning. They should be distinguished from objective academic indicators, such as official course grades, examination scores, or independently assessed learning gains.

This distinction is methodologically important. Students' perceptions can provide useful information about their experiences, but self-reported outcomes may be influenced by expectations, confidence, recall, and individual interpretations of academic improvement. Therefore, any association between AI access and perceived academic outcomes should be interpreted cautiously, especially when the data are collected through a single survey.

Examining perceived academic outcomes alongside access, AI literacy, and institutional support can help clarify whether students report different experiences of AI-assisted learning under different technological and educational conditions. However, a cross-sectional study would not establish that access to AI causes improvements in academic performance. Stronger causal claims would require an appropriate longitudinal, experimental, or quasi-experimental design.

2.6. Research Gap and Conceptual Framework

The emerging literature indicates that generative AI creates new opportunities for learning while raising questions about the distribution of technological resources and AI-related capabilities among university students. Existing studies have begun to examine socioeconomic differences, digital and AI literacy, patterns of ChatGPT use, and students' perceived educational outcomes (Beckman et al., 2025; Zhang et al., 2026).

Nevertheless, additional research is needed to examine these dimensions together within specific higher education contexts. In particular, it is important to investigate how access to AI-enhanced learning technologies relates to AI literacy, how institutional support is associated with students' opportunities to use AI, and whether these factors are associated with differences in self-reported academic outcomes.

The present study addresses this research gap by proposing a multidimensional framework that integrates four principal explanatory dimensions: socioeconomic conditions, access to AI-enhanced learning technologies, AI literacy, and institutional support. These dimensions are examined in relation to self-reported academic outcomes as an indicator of students' perceived experiences of AI-assisted learning.

The proposed framework does not assume that the relationships among these variables are necessarily causal. Instead, it provides a basis for examining their associations and identifying patterns that may be relevant to understanding academic inequality in the context of AI-enhanced higher education.

The conceptual framework is organized around the following proposed relationships:

1. Socioeconomic conditions may be associated with students' access to AI-enhanced learning technologies.
2. Access to AI-enhanced learning technologies may be associated with students' AI literacy and opportunities to engage in AI-supported academic activities.
3. AI literacy may be associated with students' self-reported academic outcomes.
4. Institutional support may be associated with access to AI tools, AI literacy development, and perceived academic outcomes.
5. Socioeconomic conditions, access, AI literacy, and institutional support may jointly explain variation in self-reported academic outcomes.

These relationships should be treated as propositions to be tested, not as established findings of the present study. Their empirical evaluation will depend on the final research design, the operational definitions of the variables, the quality of the measurement instruments, and the characteristics of the student sample.

3. Research Hypotheses and Conceptual Model

3.1. Research Hypotheses

Building on the literature review, this study proposes that academic inequality associated with artificial intelligence in higher education may be related to differences in socioeconomic conditions, access to AI-enhanced learning technologies, AI literacy, and institutional support. These factors may shape students' opportunities to engage with AI-assisted learning and their perceptions of its academic value.

The proposed hypotheses are intended to examine associations among the study variables. They do not presuppose causal relationships, and their validity must be assessed using empirical data.

3.1.1. Socioeconomic Conditions and Access to AI-Enhanced Learning Technologies

Students' socioeconomic conditions may influence their ability to obtain appropriate devices, maintain reliable internet connectivity, and access AI applications with advanced functionalities. Financial resources may also determine whether students can use paid services or rely exclusively on free alternatives. These differences may result in unequal opportunities to incorporate AI tools into academic activities.

Accordingly, the following hypothesis is proposed:

- H1: Students' socioeconomic conditions are significantly associated with their access to AI-enhanced learning technologies in higher education.

3.1.2. Access to AI-Enhanced Learning Technologies and AI Literacy

Access to AI-enhanced learning technologies may provide students with opportunities to experiment with AI applications, develop familiarity with their functions, and learn how to incorporate them into academic tasks. However, access does not automatically produce AI literacy, because the development of relevant competencies may also depend on prior knowledge, educational experiences, and institutional guidance.

Based on this reasoning, the following hypothesis is proposed:

- H2: Access to AI-enhanced learning technologies is positively associated with students' AI literacy.

3.1.3. AI Literacy and Self-Reported Academic Outcomes

Students with greater AI literacy may be better equipped to formulate effective prompts, assess the reliability of generated information, identify limitations, and integrate AI-generated content into their academic work. These competencies may be associated with more favorable perceptions of AI-assisted learning.

The third hypothesis is therefore formulated as follows:

- H3: AI literacy is positively associated with students' self-reported academic outcomes.

3.1.4. Institutional Support and AI Literacy

Universities can provide training, guidance, technological resources, and clear policies that help students understand and use AI appropriately. Students who perceive greater institutional support may have more opportunities to develop AI-related competencies and to use these technologies in ways that align with their academic requirements.

Accordingly, the following hypothesis is proposed:

- H4: Perceived institutional support for AI integration is positively associated with students' AI literacy.

3.1.5. Institutional Support and Self-Reported Academic Outcomes

Institutional support may help students identify appropriate AI applications, understand academic integrity requirements, and use AI tools to complement their learning activities. Such support may be associated with more favorable perceptions of the usefulness of AI-enhanced learning technologies.

The fifth hypothesis is formulated as follows:

- **H5:** Perceived institutional support for AI integration is positively associated with students' self-reported academic outcomes.

3.1.6. Socioeconomic Conditions and Self-Reported Academic Outcomes

Socioeconomic conditions may be associated with students' access to educational resources, opportunities to develop technological competencies, and capacity to participate in AI-supported academic activities. These conditions may therefore be related to differences in students' perceived academic experiences.

The sixth hypothesis is proposed as follows:

- **H6:** Students' socioeconomic conditions are significantly associated with their self-reported academic outcomes.

This hypothesis is intentionally non-directional because socioeconomic status may be operationalized in different ways, and its association with perceived outcomes may depend on the educational context and the resources available to students.

3.2. Proposed Conceptual Model

The conceptual model integrates four principal explanatory dimensions: socioeconomic conditions, access to AI-enhanced learning technologies, AI literacy, and institutional support. Self-reported academic outcomes constitute the principal outcome variable.

The model proposes that socioeconomic conditions may be associated with access to AI technologies and perceived academic outcomes. Access may be associated with AI literacy, while institutional support may be associated with both AI literacy and self-reported academic outcomes. AI literacy is also expected to be positively associated with perceived academic outcomes.

3.3. Operational Definition of the Main Variables

To test the proposed hypotheses, each construct must be translated into observable indicators.

- Socioeconomic conditions may be measured through indicators such as perceived financial constraints, access to educational resources, employment commitments, or a suitable measure of household socioeconomic position. Sensitive financial information should be collected only when necessary and with appropriate safeguards.
- Access to AI-enhanced learning technologies may include device availability, internet reliability, frequency of access, availability of relevant AI applications, and access to advanced features. Access should be measured separately from frequency of use because having access to a tool does not necessarily mean using it regularly.
- AI literacy may include students' perceived ability to formulate prompts, evaluate AI-generated information, recognize potential errors, understand limitations, and use AI responsibly. Where possible, an established and validated instrument should be selected or adapted with appropriate permission and validation procedures.
- Perceived institutional support may include students' perceptions of the availability of AI training, clarity of institutional policies, access to approved tools, and guidance from instructors or university support services.
- Self-reported academic outcomes may include perceived understanding of course content, perceived efficiency in completing academic tasks, confidence in academic work, and perceived usefulness of AI-assisted learning. These indicators must be clearly distinguished from objective academic performance.

The measurement of these constructs should avoid treating the mere frequency of AI use as evidence of learning improvement. A student may use AI frequently without developing a deeper understanding of course content. Therefore, the study should measure the perceived academic value of AI separately from access and use frequency.

3.4. Analytical Scope and Interpretation

The proposed framework is designed to examine relationships among the study variables rather than establish that AI access causes academic inequality. If data are collected through a cross-sectional survey, the analysis will identify associations at a particular point in time. It will not establish temporal precedence or rule out alternative explanations.

Moreover, self-reported academic outcomes reflect students' perceptions and should not be interpreted as equivalent to objective academic achievement. If feasible, future research could incorporate course grades, standardized assessments, longitudinal observations, or experimental designs to provide a more comprehensive assessment of the relationship between AI use and educational outcomes.

Finally, academic inequality is broader than any single measure of perceived academic

outcomes. The proposed study focuses on differences in students' access, capabilities, institutional experiences, and perceived outcomes as dimensions relevant to AI-related inequality. Conclusions about the overall extent of academic inequality should therefore remain proportional to the variables and population actually examined.

4. Methodology

4.1. Research Design

This study proposes a quantitative, non-experimental, cross-sectional research design to examine the relationships among socioeconomic conditions, access to AI-enhanced learning technologies, AI literacy, institutional support, and self-reported academic outcomes among university students.

A quantitative approach is appropriate because the study seeks to measure theoretically defined constructs and examine statistical associations among them. The non-experimental design is intended to observe differences and relationships as they occur naturally, without manipulating students' access to AI technologies or their educational conditions.

The cross-sectional component involves collecting data during a defined period. This design can provide evidence concerning the distribution of AI-related resources and competencies and their associations with students' reported academic experiences. However, it cannot establish temporal precedence or demonstrate that access to AI technologies causes changes in academic outcomes.

The study will therefore be framed as correlational and explanatory in a statistical sense. Any interpretation of the findings will distinguish between observed associations and causal relationships.

4.2. Study Setting and Target Population

The target population will consist of students enrolled in undergraduate programs at higher education institutions in Peru. The final institutional setting, participating universities, academic disciplines, and eligibility criteria must be specified before recruitment begins.

Eligible participants will be students who are currently enrolled in a participating higher education institution, are able to provide informed consent, and can complete the questionnaire in the language in which the instrument has been validated.

Previous experience using generative AI will not necessarily be an inclusion requirement. Including students who rarely or never use AI may be important for identifying barriers to access and distinguishing between limited use caused by restricted access and limited use caused by personal preferences or academic policies.

The study should record relevant participant characteristics, such as age group, academic year, field of study, and other theoretically justified demographic variables. Socioeconomic information should be collected in a manner that is proportionate to the research objectives and consistent with applicable ethical requirements.

The participating institutions and target population will be identified according to feasibility, institutional authorization, and the availability of an appropriate sampling frame.

4.3. Sampling Strategy and Sample Size

The sampling strategy will depend on the number of participating institutions, access to student enrollment records, available resources, and the intended scope of inference.

Where institutional collaboration and an adequate sampling frame are available, stratified sampling may be considered. Relevant strata could include institution, academic discipline, or academic year, depending on the study objectives and population structure. This approach could improve representation across important student groups.

If probability sampling is not feasible, a clearly documented non-probability recruitment strategy may be used. In that case, the limitations associated with selection bias and generalizability must be acknowledged, and conclusions should not be presented as representative of all Peruvian university students.

The required sample size will be determined before data collection using an *a priori* statistical power analysis. The calculation should reflect the primary hypothesis, the planned statistical test, the smallest effect considered meaningful, the desired statistical power, the significance level, the number of predictors, and any anticipated nonresponse or incomplete questionnaires.

For regression models, the calculation should consider the complete set of predictors and relevant covariates. If structural equation modeling is selected, sample-size planning should also consider model complexity, the number of indicators, measurement quality, and the estimation method.

No final sample size is specified at this stage because the primary statistical model, expected effect size, and recruitment conditions have not yet been confirmed.

4.4. Research Instrument

Data will be collected using a structured questionnaire designed to measure the principal constructs in the conceptual framework. The instrument may include five sections: participant characteristics, socioeconomic conditions, access to AI-enhanced learning technologies, AI literacy and institutional support, and self-reported academic outcomes.

Whenever possible, the study will use previously validated measurement instruments that are appropriate for the target population. If an existing instrument is adapted, the research team will document the source, permissions where required, translation or adaptation procedures, and evidence supporting its validity in the intended context.

4.4.1. Socioeconomic Conditions

This construct will capture relevant differences in students' economic and educational circumstances. Potential indicators may include perceived financial constraints, availability of educational resources, employment commitments, and access to a suitable study environment.

The final indicators will be selected according to theoretical relevance, feasibility, and participant privacy. The instrument should not collect unnecessary sensitive financial information.

4.4.2. Access to AI-Enhanced Learning Technologies

This construct will assess students' opportunities to access AI applications for academic purposes. Potential indicators include:

- Availability of an appropriate personal device.
- Reliability of internet connectivity.
- Ability to access AI applications when needed.
- Availability of advanced or paid AI features.
- Frequency of access to AI tools for academic activities.
- Barriers that prevent or restrict the use of these technologies.

Access and frequency of use will be measured separately. This distinction is necessary because students may have access to AI tools without using them frequently, while others may use them despite significant technological or financial constraints.

4.4.3. AI Literacy

AI literacy will be assessed through indicators related to students' ability to interact with AI systems critically and responsibly. Potential dimensions include understanding the limitations of AI-generated information, evaluating the reliability of responses, formulating appropriate prompts, identifying possible inaccuracies, and recognizing ethical concerns.

The study should prioritize an established instrument with evidence of validity and reliability. Any adaptation will require appropriate assessment of its suitability for university students in the selected context.

4.4.4. Perceived Institutional Support

Institutional support will be measured through students' perceptions of the guidance and resources their universities provide for academic AI use. Potential indicators include the availability of AI training, clarity of institutional policies, access to approved applications, guidance from instructors, and opportunities to learn about responsible AI use.

The questionnaire should distinguish between support that is formally available and support that students actually know about or perceive as accessible.

4.4.5. Self-Reported Academic Outcomes

This construct will assess students' perceptions of the academic value of AI-enhanced learning technologies. Potential indicators include perceived understanding of course content, perceived efficiency in completing academic tasks, confidence in academic work, and perceived usefulness of AI-supported learning activities.

These indicators will be interpreted as self-reported perceptions rather than objective evidence of academic achievement. If access to official academic records is feasible and ethically authorized, future analyses may incorporate independent indicators such as course grades or standardized assessment results.

4.5. Instrument Validation and Reliability

Before the main data collection, the questionnaire will undergo a systematic evaluation of its content, clarity, and suitability for the target population.

First, expert review may be used to assess the relevance and comprehensiveness of the items in relation to the conceptual definitions of the constructs. Experts should have appropriate knowledge of educational research, AI in higher education, measurement, or related fields.

Second, cognitive interviews or a small pilot study may be conducted to identify ambiguous wording, response difficulties, and potential problems with the questionnaire's organization. The pilot sample should be suitable for testing feasibility and comprehensibility; it should not automatically be treated as part of the main analytical sample.

Third, the measurement properties of the final instrument will be evaluated using methods appropriate to the data and scale structure. Internal consistency may be examined using coefficients such as McDonald's omega or Cronbach's alpha when their assumptions are reasonably satisfied. Construct validity should be assessed using suitable factor-analytic procedures when the sample size and measurement design permit.

Reliability coefficients alone will not be considered sufficient evidence that a scale is valid. The dimensionality of the instrument, item performance, and theoretical coherence of each construct will also be examined.

If the questionnaire is translated or substantially adapted, the research team will document the translation procedure and provide evidence that the resulting items are appropriate for the intended population.

4.6. Data Collection Procedure

Data collection will begin after the necessary institutional permissions and ethical approvals have been obtained.

Eligible students will receive an invitation explaining the purpose of the study, the voluntary nature of participation, the estimated completion time, the intended use of the data, and the procedures for protecting confidentiality.

The questionnaire may be administered electronically or in another accessible format, depending on the conditions of the participating institutions. Electronic administration may facilitate data management, but the research team should consider whether online-only recruitment could exclude students with limited connectivity and thereby reproduce the inequality under investigation.

To reduce avoidable participation barriers, the data collection procedure should provide reasonable accessibility accommodations and avoid requiring students to use a particular paid AI application to participate.

The research team will establish procedures for identifying duplicate submissions, monitoring missing data, and applying predefined data-quality criteria. Any exclusions will be documented transparently.

Participation will be voluntary. Where required by the approved protocol, informed consent will be obtained before the questionnaire begins.

4.7. Statistical Analysis

The statistical analysis will be conducted in stages, following the research questions and the prespecified hypotheses.

4.7.1. Preliminary Data Analysis

The initial analysis will examine the completeness, consistency, and distribution of the collected data. It will identify missing observations, potential duplicate submissions, unusual response patterns, and possible data-entry errors.

Descriptive statistics will summarize participant characteristics and the principal study variables. Depending on the measurement level and distribution, results may be reported using frequencies, percentages, means, standard deviations, medians, and interquartile ranges.

Missing data will be assessed to determine their extent and plausible patterns. The approach to handling missing observations will be selected according to the amount and nature of the missingness and the assumptions of the chosen statistical method.

4.7.2. Measurement Assessment

Where established multi-item scales are used, the analysis will examine their reliability and, when appropriate, their factor structure. Exploratory factor analysis may be considered when the dimensional structure of an adapted instrument is uncertain. Confirmatory factor analysis may be appropriate when a theoretically specified measurement model is available and the sample and data support its estimation.

These procedures will be selected according to the measurement objectives rather than applied automatically. Any modifications to the instrument or measurement model will be documented and justified.

4.7.3. Bivariate Analysis

Bivariate analyses will be used to examine initial relationships among socioeconomic conditions, access to AI-enhanced learning technologies, AI literacy, institutional support, and self-reported academic outcomes.

The choice of statistical test will depend on the measurement level, distribution, and assumptions of the variables. Pearson or Spearman correlation coefficients may be used for suitable pairs of variables. Group comparisons may be conducted when theoretically relevant and statistically appropriate.

Effect sizes and confidence intervals will be reported where possible, rather than relying exclusively on statistical significance.

4.7.4. Multivariable Regression Analysis

Multivariable regression will be considered the principal method for examining the proposed relationships, provided that the assumptions of the selected model are satisfied.

For example, if the primary outcome is measured using a sufficiently continuous composite score, multiple linear regression may be used to examine its association with AI literacy, institutional support, socioeconomic conditions, and access to AI-enhanced learning technologies.

Potential covariates may include academic year, field of study, institution, and other variables justified by the research questions and theoretical framework. Their inclusion should be prespecified where feasible and should not be based solely on whether they produce statistically significant results.

The analysis will examine model assumptions, multicollinearity, influential observations, and the suitability of the outcome measure for the selected model. Regression coefficients, confidence intervals, model fit, and relevant effect-size measures will be reported.

The hypotheses concerning access and AI literacy may require additional regression models with those constructs as outcomes. The precise models will be specified before the main

analysis.

4.7.5. Additional Analyses

If the sample size, measurement properties, and theoretical model support it, structural equation modeling may be considered to examine multiple relationships among latent constructs simultaneously.

However, structural equation modeling will not be used merely to make the analysis appear more sophisticated. A transparent set of regression models may be more appropriate when the sample or measurement structure does not support a complex latent-variable model.

If analyses are conducted across different student groups, measurement comparability should be assessed before interpreting group differences. Subgroup analyses should be theoretically justified and interpreted cautiously, particularly when some groups have small sample sizes.

4.8. Ethical Considerations

The study will follow the ethical requirements applicable to research involving university students and the policies of the participating institutions.

Before participation, students will be informed about the purpose of the study, the voluntary nature of participation, the intended use of the data, and any foreseeable risks. The consent procedure will explain that participation or nonparticipation will not affect students' grades, access to university services, or relationship with their instructors.

Data will be collected and stored using appropriate security measures. Personally identifying information will not be collected unless necessary for an explicitly justified purpose. If identifying information is required for recruitment or follow-up, it should be stored separately from research responses whenever feasible.

The study will avoid collecting unnecessary sensitive information and will report findings in a manner that reduces the risk of identifying individual participants or small groups.

Because the research examines differences in technological access and academic opportunities, results should be presented without stigmatizing students with fewer resources. The objective is to identify structural barriers and inform equitable educational practices, not to characterize disadvantaged students as less capable.

The research protocol will be submitted to the appropriate ethics committee or institutional review body before data collection begins, where required. The manuscript will report the actual approval details and procedures once they have been obtained; no approval number or completed ethical procedure will be claimed in advance.

4.9. Methodological Limitations

Several methodological limitations should be considered when interpreting the eventual findings.

First, a cross-sectional design cannot establish the temporal sequence of the relationships among socioeconomic conditions, AI access, AI literacy, institutional support, and academic outcomes. Observed associations may reflect reciprocal relationships or unmeasured factors.

Second, self-reported measures may be affected by recall errors, social desirability, and differences in how students interpret the questionnaire items. Where feasible, future research could incorporate objective indicators of academic performance and direct assessments of AI literacy.

Third, a non-probability sample would limit the extent to which findings could be generalized beyond the participating students. Recruitment procedures and sample characteristics must therefore be reported transparently.

Fourth, AI tools and institutional policies change rapidly. The findings will reflect the technologies and educational conditions available during the data collection period and may not generalize unchanged to later periods.

Finally, the operationalization of academic inequality will depend on the measures included in the study. Associations involving self-reported academic outcomes cannot, on their own, establish that AI has increased or reduced inequality in objective educational achievement.

5. Results

5.1. Overview of the results section

The results section will present the empirical findings obtained from the analysis of the collected data. The analysis will follow the research questions and hypotheses established in the conceptual framework, focusing on socioeconomic conditions, access to AI-enhanced learning technologies, AI literacy, institutional support, and self-reported academic outcomes.

The results will be organized into five subsections: participant characteristics, descriptive statistics, measurement reliability and validity, bivariate associations, and multivariable regression analyses.

Descriptive analyses will first characterize the participating students and the distribution of the principal study variables. Subsequent analyses will examine the relationships among the variables and assess the proposed hypotheses.

The findings will be reported using appropriate statistical indicators, including frequencies, percentages, means, standard deviations, correlation coefficients, regression coefficients, confidence intervals, and relevant measures of model fit. The statistical procedures used will depend on the final measurement instruments and the characteristics of the collected data.

5.2. Participant Characteristics

The first analysis will describe the demographic and academic characteristics of the participating students. Relevant characteristics may include age group, academic year, field of study, institution, and other variables justified by the research objectives.

Socioeconomic characteristics and students' access to technological resources will also be summarized to provide context for interpreting differences in AI-related educational opportunities.

The final manuscript will report the number of students invited to participate, the number of completed questionnaires, the number of observations excluded from the analysis, and the final analytical sample. Any exclusions will be explained according to predefined data-quality criteria.

5.3. Descriptive Statistics of the Main Study Variables

Descriptive analyses will summarize the distribution of socioeconomic conditions, access to AI-enhanced learning technologies, AI literacy, institutional support, and self-reported academic outcomes.

These analyses will identify patterns in students' reported access to technological resources and their perceptions of their ability to use AI for academic purposes.

For continuous or approximately continuous composite scores, means and standard deviations may be reported when appropriate. Medians and interquartile ranges may be used when distributions are substantially skewed. Categorical variables will be summarized using frequencies and percentages.

The results will distinguish between access to AI technologies and frequency of use, since these represent related but conceptually different dimensions.

5.4. Reliability and Validity of the Measurement Instruments

Before testing the research hypotheses, the measurement properties of the questionnaire will be evaluated.

Internal consistency will be assessed for multi-item scales when appropriate, using suitable reliability coefficients. Evidence concerning construct validity will be examined according to the measurement model and the characteristics of the data.

Where factor analysis is justified, the results will describe the relevant factor structure, item performance, and indicators used to evaluate the measurement model.

Only analyses that are actually conducted will be reported. The manuscript will not claim that an instrument demonstrated adequate reliability or validity until the corresponding empirical evidence is available.

5.5. Associations Among the Study Variables

Bivariate analyses will examine the relationships among socioeconomic conditions, access to AI-enhanced learning technologies, AI literacy, institutional support, and self-reported academic outcomes.

Correlation coefficients and their confidence intervals will be reported where appropriate. The direction and magnitude of the observed associations will be interpreted in relation to the research questions, without assuming that statistical association establishes causality.

The analysis will pay particular attention to whether access to AI technologies is associated with AI literacy and whether AI literacy is associated with students' perceived academic outcomes.

5.6. Multivariable Regression Analyses

Multivariable regression models will be used to examine the relationships specified in the research hypotheses, provided that the selected outcome measures and statistical assumptions support the planned analyses.

The principal outcome model will examine whether AI literacy, institutional support, access to AI-enhanced learning technologies, and socioeconomic conditions are associated with self-reported academic outcomes.

Additional models may examine the association between socioeconomic conditions and technological access, as well as the relationships between technological access and AI literacy and between institutional support and AI literacy.

The final report will present the estimated coefficients, confidence intervals, statistical significance indicators, and appropriate measures of model fit. Potential confounding variables will be selected based on theoretical considerations and the research design.

The results will be interpreted as associations unless the design provides sufficient grounds for stronger causal conclusions.

5.7. Summary of Hypothesis Testing

The final subsection will summarize the empirical evidence concerning each hypothesis.

Each hypothesis will be classified according to the results of the prespecified statistical analysis. The interpretation will consider the direction and magnitude of the estimated relationship, the confidence interval, and the degree of statistical uncertainty.

A statistically nonsignificant result will not automatically be interpreted as evidence that no relationship exists. Likewise, a statistically significant association will not necessarily indicate a practically important effect.

The results will provide the empirical basis for the discussion, where the findings will be compared with previous research and their theoretical and practical implications will be examined.

6. Discussion

6.1. Understanding academic inequality in the context of artificial intelligence

The increasing integration of artificial intelligence into higher education requires a broader understanding of academic inequality. Although AI-enhanced learning technologies may expand access to educational resources, their potential benefits depend on the conditions under which students access, understand, and use these tools. Consequently, the availability of AI applications should not be interpreted as evidence that educational opportunities have become more equitable.

The conceptual framework developed in this study considers academic inequality in relation to socioeconomic conditions, access to AI-enhanced learning technologies, AI literacy, institutional support, and self-reported academic outcomes. This multidimensional perspective recognizes that students may encounter different opportunities to benefit from AI even when they are enrolled in the same institution or have access to the same learning platforms.

The proposed approach is consistent with research examining the emergence of a generative AI divide among university students. Beckman et al. (2025) emphasized the importance of understanding differences in students' knowledge, capabilities, and engagement with generative AI. Similarly, Zhang et al. (2026) examined the relationships among socioeconomic status, AI literacy, ChatGPT activities, and perceived educational outcomes from a digital divide perspective.

Building on this literature, the present study proposes that AI-related academic inequality should be investigated as a combination of technological, individual, and institutional conditions. The empirical value of this approach will depend on whether the proposed relationships are supported by data from the target population.

6.2. Socioeconomic Conditions and Unequal Access to AI Technologies

Socioeconomic conditions may influence students' ability to access suitable devices, maintain reliable internet connectivity, and use AI applications with different levels of functionality. Financial constraints may also limit students' opportunities to purchase subscriptions or access complementary educational resources.

These differences are relevant because access to AI technologies may determine the range of learning activities students can undertake with technological assistance. Nevertheless, socioeconomic status should not be treated as a complete explanation of students' technological opportunities. Institutional resources, geographical conditions, personal preferences, and existing digital competencies may also influence access and use.

The proposed first hypothesis examines whether socioeconomic conditions are associated with access to AI-enhanced learning technologies. If this association is supported by the empirical findings, it would provide evidence that students' material circumstances are relevant to understanding differences in their AI-related educational opportunities.

If the association is weak or statistically nonsignificant, alternative explanations would need to be considered. For example, participating institutions might provide comparable access to AI tools, or students might obtain access through free applications and other resources. Such findings would require interpretation in light of the sampling strategy, the measures used, and the characteristics of the educational context.

In either case, the analysis should distinguish between access to AI tools and the ability to use them effectively. This distinction is essential for avoiding the assumption that providing technology alone is sufficient to address educational inequality.

6.3. AI Literacy and the Unequal Capacity to Benefit from Technology

Access to AI technologies does not necessarily translate into the ability to use them effectively. AI literacy involves understanding the capabilities and limitations of AI systems, evaluating generated information, identifying potential errors, and applying the technology in accordance with academic and ethical expectations.

Zhang et al. (2026) examined differences in AI literacy and patterns of ChatGPT engagement among college students. Their work provides a relevant foundation for investigating whether students' competencies are associated with how they use AI for academic purposes.

The second hypothesis proposes a positive association between access to AI-enhanced learning technologies and AI literacy. If supported, this relationship would suggest that students with greater opportunities to access AI tools may also report stronger AI-related competencies. However, a cross-sectional association would not establish that access itself develops literacy. Students with greater prior technological knowledge may be more likely to obtain and use AI tools, while other educational and socioeconomic factors may influence both variables.

The third hypothesis proposes that AI literacy is positively associated with self-reported academic outcomes. This relationship may reflect students' capacity to use AI to clarify concepts, organize information, evaluate alternative explanations, or receive preliminary feedback.

However, AI literacy should not be understood simply as the ability to generate responses or

use sophisticated prompts. Critical evaluation, awareness of limitations, and appropriate independent judgment are equally important. A student who can generate extensive AI-supported content without verifying its accuracy may not necessarily experience better learning outcomes.

For this reason, the interpretation of the findings should consider the specific dimensions of AI literacy measured by the instrument. If the scale primarily assesses self-confidence rather than demonstrated competence, the results should be described as perceived AI literacy rather than objective proficiency.

6.4. Institutional Support as a Condition for Equitable AI Integration

Universities influence the conditions under which students learn about and use AI technologies. Institutional support may include access to digital resources, training opportunities, guidance from instructors, clear policies, and explanations of responsible AI use.

UNESCO's guidance on generative AI in education and research emphasizes the importance of a human-centred approach to the integration of these technologies, including capacity development and appropriate safeguards (Miao & Holmes, 2023). Such principles support the consideration of institutional responsibilities alongside individual students' technological competencies.

The fourth hypothesis examines the association between institutional support and AI literacy. If supported, the finding would be consistent with the proposition that universities can contribute to students' development of AI-related competencies through training, guidance, and educational opportunities.

The fifth hypothesis examines the association between institutional support and self-reported academic outcomes. A positive relationship could indicate that students who perceive stronger institutional guidance also report more favorable experiences with AI-assisted learning.

Nevertheless, institutional support may be unevenly distributed, and students' perceptions of available support may not correspond directly to the services formally offered by their universities. Future analyses should therefore distinguish between the existence of institutional policies, students' awareness of those policies, and their actual ability to access relevant support.

Moreover, support should not be reduced to encouraging greater AI use. Effective institutional guidance should help students identify when AI assistance is appropriate, verify generated information, protect personal information, and maintain responsibility for their academic work.

6.5. Self-Reported Academic Outcomes and the Interpretation of AI Benefits

A central challenge in researching AI in higher education is distinguishing perceived usefulness from demonstrated educational improvement. Students may report that AI helps them complete assignments more efficiently or understand unfamiliar concepts. However, these perceptions do not necessarily establish improvements in knowledge retention, critical thinking, examination performance, or independent problem-solving.

Zhang et al. (2026) examined different forms of ChatGPT activity in relation to educational outcomes, highlighting the importance of distinguishing among patterns of engagement rather than treating all AI use as equivalent.

The present study focuses on self-reported academic outcomes because students' perceptions provide information about their experiences with AI-enhanced learning technologies. Nevertheless, these measures must be interpreted within their methodological limits.

If AI literacy and institutional support are positively associated with perceived academic outcomes, the findings would indicate that these factors are related to students' reported experiences. They would not demonstrate that AI use improves objective academic achievement.

Similarly, if access to AI technologies is associated with more favorable perceptions, this relationship could reflect differences in students' academic needs, prior achievement, confidence, or general attitudes toward technology. These alternative explanations should be considered when interpreting the findings.

Future research could strengthen the evidence by combining self-reported measures with objective academic indicators, performance-based assessments of AI literacy, and longitudinal data. Such designs would provide a more comprehensive understanding of whether unequal access to AI technologies corresponds to measurable differences in educational outcomes.

6.6. Theoretical Implications

The proposed framework contributes to the study of educational technology inequality by bringing together dimensions that are sometimes examined separately. These include material access, AI-related competencies, institutional support, and students' perceptions of academic outcomes.

First, the framework extends a narrow understanding of the digital divide by distinguishing access to technology from the capacity to use it critically and productively. This distinction is important because equal access does not necessarily produce equal educational experiences.

Second, the framework positions AI literacy as a distinct construct that may be associated with the academic value students perceive in AI-supported learning. This approach recognizes that familiarity with AI systems is not equivalent to the ability to evaluate their outputs or use them appropriately.

Third, the inclusion of institutional support emphasizes that AI-related educational opportunities are not determined exclusively by individual characteristics. Universities may shape students' opportunities through training, resource allocation, and the clarity of their guidance.

Finally, the framework treats academic inequality as a multidimensional issue that requires empirical assessment. Rather than assuming that AI inevitably increases or decreases inequality, it proposes examining the relationships among relevant social, technological, and educational factors.

These contributions remain conceptual until the proposed relationships have been evaluated using appropriate empirical data.

6.7. Practical Implications for Higher Education Institutions

The proposed framework suggests several areas that universities may consider when developing AI integration strategies.

First, institutions should assess whether students have reliable access to the devices, connectivity, and applications required for their academic activities. Where barriers are identified, universities may consider improving access to suitable resources or providing alternatives that do not depend on paid subscriptions.

Second, AI literacy development should be integrated into educational support. Training can address the evaluation of AI-generated information, responsible use, prompt formulation, recognition of limitations, and the verification of sources.

Third, institutions should communicate clear and consistent expectations concerning AI use in coursework, research, assessment, and academic writing. Students should understand which activities are permitted, how AI assistance should be disclosed when required, and which academic responsibilities remain their own.

Fourth, universities should evaluate the accessibility of their AI policies and training opportunities. A policy may exist without reaching the students who need it most. Institutions should therefore examine whether support is available across disciplines and student groups.

Fifth, AI integration strategies should be evaluated using evidence rather than technological adoption alone. The number of AI applications available or the frequency with which students use them does not establish that learning has improved or that educational opportunities have become more equitable.

These implications should be refined according to the empirical findings and the context of the participating institutions. The study should not recommend a specific intervention as effective unless sufficient evidence supports that conclusion.

6.8. Limitations and Directions for Future Research

Several limitations should be considered when interpreting the proposed research framework and any future empirical findings.

First, a cross-sectional design would limit the ability to establish temporal relationships among socioeconomic conditions, access, AI literacy, institutional support, and academic outcomes. Longitudinal research could examine whether changes in access or training are followed by changes in students' competencies and educational experiences.

Second, reliance on self-reported measures may introduce common-method bias, social desirability effects, and differences in how participants understand questionnaire items. Future research could combine surveys with performance-based AI literacy assessments and objective academic indicators.

Third, the representativeness of the sample will depend on the recruitment strategy. Findings from a convenience sample at a limited number of universities should not automatically be generalized to the entire higher education population of Peru or other countries.

Fourth, the rapid development of AI technologies means that students' opportunities and patterns of use may change over time. Replication studies will be necessary to examine whether the proposed relationships remain consistent as applications, institutional policies, and educational practices evolve.

Fifth, the study's conclusions will be limited by the operational definition of academic inequality. Measures of access and self-reported outcomes can reveal important differences in students' experiences, but they do not capture every dimension of educational inequality.

Future research should examine the proposed relationships across different institutional settings, academic disciplines, and socioeconomic groups. Longitudinal or quasi-experimental designs may also help clarify whether interventions aimed at improving access and AI literacy are associated with changes in learning outcomes.

6.9. Concluding Interpretation

The integration of AI into higher education creates opportunities to support learning while raising questions about the distribution of technological resources, competencies, and institutional assistance. Understanding these developments requires attention not only to who has access to AI but also to who can use it critically and under what educational conditions.

The conceptual framework presented in this study provides a basis for examining how socioeconomic conditions, access to AI-enhanced learning technologies, AI literacy, and institutional support are associated with students' self-reported academic outcomes. Its contribution will ultimately depend on the quality of the empirical design, the validity of the measurements, and the transparency of the statistical analysis.

By examining these relationships, the study aims to inform a more equitable approach to AI integration in higher education. The central objective is to determine whether and how differences in technological and institutional conditions correspond to differences in students' opportunities to benefit from AI-assisted learning.

7. Conclusion

Artificial intelligence is becoming increasingly relevant to higher education, creating new possibilities for academic support while raising important questions about equity. The availability of AI-enhanced learning technologies does not necessarily guarantee that all students have equivalent opportunities to benefit from them. Differences in socioeconomic conditions, technological access, AI literacy, and institutional support may shape students' experiences with these technologies.

This study proposes a multidimensional framework for examining the relationships among these factors and self-reported academic outcomes. By distinguishing technological access from AI literacy and institutional support, the framework moves beyond a narrow understanding of the digital divide and emphasizes the importance of the conditions under which students use AI for academic purposes.

The proposed hypotheses provide a basis for empirically investigating whether socioeconomic conditions are associated with unequal access, whether access is related to AI literacy, and whether AI literacy and institutional support are associated with students' perceived academic outcomes. These relationships must be evaluated using validated measurement instruments and an appropriate research design.

The practical implications concern the development of equitable AI integration strategies in higher education. Universities should consider students' access to technological resources, opportunities to develop AI literacy, the availability of institutional guidance, and the evaluation of educational outcomes. Such strategies should prioritize critical and responsible engagement with AI rather than technological adoption alone.

The study also recognizes that self-reported academic outcomes cannot independently establish improvements in objective academic performance. Future empirical research should therefore consider combining students' perceptions with appropriate performance-based assessments and, where feasible, longitudinal data.

Ultimately, whether AI reduces or reinforces academic inequality depends on the conditions under which it is implemented and used. By examining the relationships among access, capabilities, institutional support, and perceived outcomes, this research framework seeks to contribute to a more evidence-based and equitable approach to AI in higher education.

CRediT authorship contribution statement

Merith Eva Bardales Meneces: Conceptualization, Methodology, Writing – original draft.
Alexandra Rivas Meza: Conceptualization, Investigation, Theoretical framework.
Julio Andres Palomino Lopez: Methodology, Validation, Formal analysis planning.
Amelia Cristina Mamani Huanca: Writing – review & editing, Validation.
(Note: Provisional contribution statement to be confirmed by all authors prior to final submission.)

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Ethics statement

Before data collection begins, the research protocol will be submitted to the appropriate institutional ethics committee or institutional review board for evaluation and approval, where required. Participation will be voluntary, and written informed consent will be obtained from all participants before they complete the questionnaire.

Data availability

No empirical dataset is currently available as data collection has not yet been completed. Following completion of the study, anonymized data may be made available from the

corresponding author upon reasonable academic request, in accordance with participant consent and institutional data protection policies.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used generative artificial intelligence tools in order to assist with preliminary drafting, organization, and language refinement. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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