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Digital Meritocracy or Hidden Inequality? AI-Assisted Thesis Writing among Low-Income Sports Students under the Common Prosperity Policy in China

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Abstract

This study examines the impact of Gen AI tools on academic equity among undergraduate sports students in China under the common prosperity policy. Using a mixed-methods approach, 25 graduation theses each from low-income and non-low-income groups at a university in Yunnan, China were collected and semi-structured interviews were conducted with 18 students. Quantitative content analysis and Mann-Whitney U test were used to compare group differences. Quantitative analysis showed that low-income students lagged significantly behind non-low-income students in originality, analytical depth, structural coherence, and AI trace evidence, while no significant difference was observed in disciplinary appropriateness. Qualitative findings revealed that these gaps were driven by multiple usage strategies and resource access pathways. The results indicated that the spread of AI technology has not automatically eliminated educational inequality but instead reproduces the digital divide through access conditions, usage skills, algorithmic register bias, and unbalanced educational support. Based on this, four intervention strategies were proposed: centrally deploying a campus-wide AI writing platform, embedding AI literacy training into writing courses, improving AI usage guidelines and feedback mechanisms, and implementing human-machine collaborative teaching models to harness AI's positive potential for educational equity.

Keywords: Common prosperity, Digital divide, Educational inequality, Gen AI, Sports students

Introduction

The advent of technology is often accompanied by two contrasting prophecies, with one side seeing it as a bridge to close the divide and the other fearing that it will become a new accomplice to inequality. This is especially true in education. Artificial intelligence, especially Gen AI tools such as ChatGPT, seem to give us unprecedented hope for equity: simply by owning an internet-connected device, every student seems to have equitable access to the world's most advanced writing instruction (Yu et al., 2024). Yet historical experience reminds us that technology is never truly neutral; it tends to favor groups that already have the resources, skills, and social capital (Addy et al., 2024; Carter et al., 2020). Perhaps there is an unspoken rule behind every technological miracle: those who have more are always more likely to have more.

In contemporary China, "Common Prosperity" has been transformed from an ideal slogan into a serious national strategy. It does not only emphasize the distribution of material wealth, but also focuses on the fair sharing of everyone's abilities, opportunities, and resources, of which educational equity is especially at the core (Wang & Ruan, 2024). In the digital age, Gen AI is widely seen as a natural fit for this grand ideal. However, there is often an insurmountable abyss between the ideal and the reality: true equity, not only in terms of tools and resources, but also in terms of the ability to truly use, harness, and transform those tools (Robeyns, 2006; Scheerder et al., 2017). In other words, the real divide is not one of access to technology, but one of how to utilize it. At the intersection of such complex times, low-income students in sports majors are a special but important group who are often at the beginning of an academically unprepared career, but are forced to balance classroom learning with test preparation in an extremely intense training regimen (Vance, 2019). In their world, time is a scarce luxury and physical exhaustion often crowds out mental space. In theory, AI tools seem to ease the burden of writing for them, but in practice, the reality of technology use is far more brutal and complex than imagined. How can a technology that is supposed to liberate them be truly transformed into their academic capabilities rather than a trap and burden? This is an academic question and a profound test of social justice.

Nevertheless, few studies have specifically focused on the real challenges and underlying mechanisms of Gen AI tool use among low-income groups specializing in sports, and there is a lack of empirical explorations that combine technology use with China's Common Prosperity policy goals. It is against this background that this study was conducted. We adopt an interpretive mixed-methods approach, using Van Dijk's (2006) digital divide model and Sen's capability approach (Robeyns, 2005) as theoretical perspectives, focusing on low-income sports students and exploring in-depth the practical differences in the actual use of AI-assisted writing tools, the underlying mechanisms, and the possible coping strategies. Our goal is not only to understand the problem, but also to find out how to cross that hidden passage between technological wonders and real-life dilemmas. As the saying goes: "We shape our tools, and thereafter our tools shape us" (Hurme & Jouhki, 2017). This study hopes to answer the question: How can we shape AI technology so that it can actually shape a more equitable future?

Literature review

The development of digital technology continues to change the landscape of education, but it also raises persistent issues of inequality (Aissaoui, 2021). Digital divide theory has evolved from the "access gap" and "skills gap" to a focus on the "outcomes gap" (Scheerder et al., 2017 ; Van Dijk, 2006). Especially in the age of AI, the third-generation digital divide highlights the gap between technology use and educational outcomes for different social groups (Carter et al., 2020 ; Jiang & Shao, 2024). Although AI tools have improved the efficiency and quality of learning as a whole, there are clear socioeconomic contextual differences in students' actual benefits (Bohnert & Gracia, 2023; Yu et al., 2024). This stems not only from technology access, but also from deeper factors of social structure, cultural capital, and institutional support: low-income groups are prone to superficial participation and deep exclusion when lacking institutional and cultural support (Khowaja et al., 2024 ; Mac Fadden et al., 2024; Rydzewski, 2025). And this structural imbalance is also significantly exacerbated by regional differences in teacher technology training (Herold, 2017).

The widespread use of generative AI further reinforces class stratification caused by technology, generating the phenomenon of so-called "digital meritocracy", whereby technology may entrench or even exacerbate existing social disparities in terms of resources, abilities, and cultural capital (Chang, 2020). The narrative of technological neutrality ignores socioeconomic and resource access differences, leading to the possibility that technology may instead reinforce educational inequalities (Addy et al., 2024). The algorithmic bias of educational AI systems also negatively labels disadvantaged groups during data training, undermining their academic subjectivity and self-confidence (Baker & Hawn, 2022; Pyle & Andalibi, 2021). In addition, ethical distress such as the phenomenon of AI guilt proposed by Qu and Wang (2025), structural biases in the data training process (Kizilcec & Nee, 2022), as well as linguistic and disciplinary cultural differences, have further exacerbated inequalities in the use of AI (Muñoz- Basols et al., 2024; Qu et al., 2024). Empirical studies by Yu et al. (2024) and Bohnert and Gracia (2023) also confirmed the significant impact of socioeconomic status on the effectiveness of AI tools in education.

Therefore, measuring the contribution of AI technology to educational equity cannot be limited to the level of resource provision, but needs to focus on whether individuals can actually transform technology into effective practical capabilities (Otto & Ziegler, 2006; Zheng, 2009). Sen's capability approach emphasizes that the transformation of resources into practical capabilities depends on the synergy of social, institutional, and individual environments (Robeyns, 2005). Difficulties with academic writing are particularly evident in sports program students, where traditional sports talent cultivation often favors non-physical forms of academics, making it difficult for students to express their understanding of physicality through written assignments (McVeigh & Waring, 2023), and this lack of expressive ability may also limit their effective use of writing-based AI tools. Transformative factors such as individual learning habits, technological dependence, and institutional environments (Limaj & Bilali, 2018), as well as the synergistic effects of cultural capital and social institutions (Gesser-Edelsburg et al., 2024) further determine the educational equity potential of AI tools. The key to judging AI empowerment of individuals is whether it truly extends users' autonomy and choice (Litschka, 2025), and the essence of current digital poverty is also being characterized by the lack of capacity to convert technology into outcomes (Baxter & Hinton, 2025). The reality of technology use barriers (e.g., unstable networks, lack of data, limited study time) for sports students further highlights such capability transformation challenge (Lobo, 2023), although Lee and Lee (2021) found that personalized feedback and evaluation may be effective in mitigating this problem. Thus, the capability approach reminds us that AI educational equity must focus on whether students can actually achieve effective translation of technological resources.

China's "Common Prosperity" policy emphasizes the promotion of educational equity and social integration through digital technology (Ministry of Education of the People's Republic of China, 2025). In reality, however, the uneven allocation of regional educational resources (Wang & Ruan, 2024) and the neglect of regional differences in ICT development (Zhou et al., 2019) still pose serious challenges. Therefore, the diffusion of Gen AI technologies must be accompanied by appropriate policy and institutional support to realize a true educational equity effect (Khowaja et al., 2024 ; Rasheed et al., 2025; Zhang & Wang, 2024). As Dunford (2022) points out, the realization of common prosperity not only relies on economic redistribution, but also requires institutional arrangements to safeguard the development opportunities and public services for disadvantaged groups. Without long-term digital literacy development and institutional investment, AI may exacerbate the marginalization of disadvantaged groups (Chen et al., 2024; Dabie, 2025). Inadequate digital infrastructure and users' lack of digital literacy also seriously limit the achievement of common prosperity goals (Wei et al., 2025), while different governance models significantly affect the equity in the utility of AI tools (Roberts et al., 2023). In addition, gender, discipline , and cultural background further influence AI adoption and use (Elshaer et al., 2024). Therefore, under the common prosperity policy, achieving AI-based educational equity requires both institutional support and mechanisms that enhance students' capability conversion, ensuring that AI is not merely a symbol of technological fairness but a genuine driver of educational equality.

In summary, the digital divide theory has evolved from issues of access to those of skills and, ultimately, outcomes. In the context of widespread adoption of Gen AI, the challenge of educational equity has become increasingly complex, and technological access alone can no longer compensate for inequalities caused by multidimensional factors such as socioeconomic status, digital literacy, and cultural capital. Technology is not inherently neutral, and existing studies have revealed that algorithmic bias and digital meritocracy may reinforce or even exacerbate educational disparities. Sen's capability approach reminds us that fairness in resource allocation does not mean fairness in capability conversion, and that students' social background and institutional context determine whether or not they can truly benefit from AI empowerment. However, most current research focuses on general student populations, with little attention paid to the specific challenges faced by low-income students in sports-related majors, a typically disadvantaged group. Meanwhile, there is a lack of empirical analysis regarding the use of AI-assisted writing tools in the context of China's common prosperity policy, and the practical application of the capability approach in this area remains underexplored.

To this end, this study integrates Van Dijk's (2006) three-stage model of digital divide and Sen's capability approach (Robeyns, 2005) to jointly construct an analytical framework using the common prosperity policy as the macro-institutional context (see Figure 1). The digital divide theory emphasizes the progressive structure from access to usage skills to actual outcomes, which helps to reveal the differentiation paths of emerging technologies such as AI in different socioeconomic backgrounds; the capability approach further emphasizes whether students can effectively convert available resources into real capabilities that enable them to achieve their values and goals, focusing on the influence of social, institutional, and individual characteristics on this conversion process. By combining these two perspectives, this study not only examines differences in technology access and usage, but also investigates the deeper structural barriers that affect low-income sports students' ability to transform AI-assisted writing tools into meaningful academic capabilities. In doing so, it seeks to assess whether the deployment of AI tools truly serves educational equity and meets the institutional demands of China's common prosperity agenda. Specifically, this study aims to answer the following research questions:

(1) In the process of completing graduation theses with the assistance of AI tools, do significant differences exist between low-income sports students and their non-low-income peers in terms of tool usage, actual capability development, and academic outcomes?

(2) If such differences exist, what are the underlying mechanisms and structural factors? What specific challenges do low-income sports students face in the use of AI tools?

(3) Under the policy goal of common prosperity, how can institutional interventions and educational practices enable low-income sports students to more equitably benefit from AI tools, thereby improving their academic capabilities and outcomes to achieve educational equity?

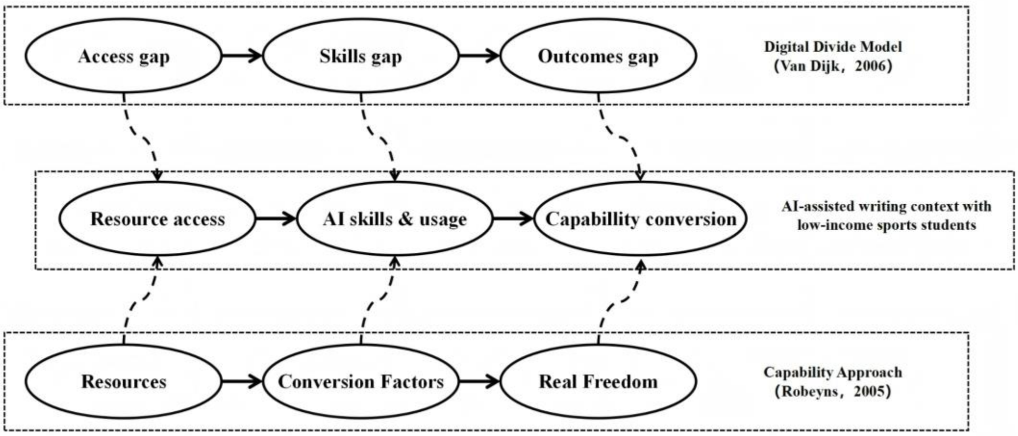

Figure 1 Theoretical framework

Methodology

Research design

This study adopts an explanatory sequential mixed methods design (Creswell & Clark, 2017) to systematically identify and explain the differences in the effectiveness of Gen AI writing tools among students from different socioeconomic backgrounds. The design consists of two phases, the first phase is a quantitative content analysis, aimed at comparing differences in performance between low-income and non-low-income sports students' ability to use AI tools during the graduation thesis writing process, and the second phase involves qualitative interviews and thematic analysis, utilizing semi-structured interviews to deeply analyze the mechanisms behind the differences, including structural factors such as digital skills, transformation ability, and institutional support.

Phase I: Quantitative content analysis

The quantitative data in this study were drawn from the graduation theses of undergraduate students enrolled in sports-related majors at a university in Yunnan Province, China, during the 2024-2025 academic year. A total of 244 students completed graduation theses during this period, among whom 52 were officially classified as economically disadvantaged according to the university's financial aid records. To ensure scientific rigor and comparability, a stratified sampling was adopted. Based on the list of economically disadvantaged students provided by the student affairs office and compiled according to the university's standardized annual financial aid assessment system, which is based on family income per capita, verified documentation, and multi-level administrative review consistent with national standards for identifying economically disadvantaged students in higher education, 25 low-income sports students were randomly selected as the study group; another 25 students not classified as economically disadvantaged were randomly selected as the control group. All their theses were written in Chinese, and the data collection took place from March to May 2025. All samples were the first drafts officially submitted to advisors, with highly consistent writing requirements, course training, and thesis evaluation criteria. Each participant had taken one semester of compulsory thesis writing courses, and independently wrote their first draft following topic approval by their advisor. Thus, these drafts best reflect the original features of AI-assisted writing without external revision intervention. Furthermore, the research team confirmed through communication with the students that all included theses involved some degree of AI-assisted writing, thereby meeting the basic requirement for analyzing AI writing behavior. All participants gave informed consent for their theses to be used anonymously in this study. The sample size and group balance were further verified through a post hoc power analysis using G*Power 3.1.9.7 (Faul et al., 2007), which yielded a statistical power ($1-\beta$) of 0.993 with a large expected effect size (Cohen's $d = 1.20$, $\alpha = 0.05$). The analysis indicated that a minimum total sample of 18 participants (9 per group) would be required to achieve a conventional power level of 0.80 under these parameters. This indicates that the selected sample size is sufficient for detecting between-group differences within an exploratory mixed-methods framework and aligns with established recommendations for group comparison research (Creswell & Clark, 2017).

To scientifically assess the impact of AI-assisted writing on students' thesis outcomes and to identify differences in writing performance across socioeconomic groups, this study developed a theory-driven scoring framework. The framework is grounded in Van Dijk's (2006) three-stage digital divide model and Sen's capability approach (Robeyns, 2006). The underlying rationale is that technological access represents only superficial equality, while the real difference lies in whether students can effectively use AI and convert its resources into meaningful academic output. Accordingly, this study proposed five scoring criteria based on two core dimensions: outcome orientation and conversion capability. (1) *Originality* assesses whether students can personalize and restructure AI-generated content, reflecting their ability to convert technological resources into authentic expression. (2) *Analytical Depth* evaluates whether the text embodies higher-order functions such as logical reasoning and critical thinking, indicating whether the AI tool was used for thought construction rather than superficial text stacking. (3) *AI Trace Evidence* measures the presence of obvious generative language traces in the text, such as entry stacking, overly generic statements, AI prompt words, etc., with higher scores representing more noticeable traces, suggesting weaker conversion capability. (4) *Structure Coherence* reflects students' ability to build clear logic and paragraph structure based on AI-assisted draft at the level of text organization, which is often dependent on their previous educational experience, language proficiency, and other contextual or individual conversion factors. (5) *Disciplinary Appropriateness* examines whether students naturally incorporate the terminology, logic, and methodology of sports into their writing, representing their freedom to manifest the functional realization in a particular disciplinary context. All five dimensions were rated on a 5-point Likert scale, and each thesis was independently and blindly evaluated by two researchers, with dimensions differing by more than one point arbitrated by a third reviewer. Evaluation criteria were standardized prior to scoring to ensure inter-rater reliability.

After both raters completed the scoring of all sample theses, their average scores were calculated, and SPSS 26.0 was used to analyze the data. Descriptive statistics were first conducted to calculate the mean and standard deviation of each scoring dimension in the low-income and non-low-income groups, in order to present the overall trends in writing performance between them. Since most dimensions did not follow a normal distribution, the Mann-Whitney U test was used to determine the statistical significance of group differences. Additionally, to visually illustrate the differences in capability structures between the groups, a bar chart was created to compare the performance characteristics of the two groups across all indicators. To ensure the reliability and measurement quality of the independent ratings by the two researchers, inter-rater consistency was examined for each item using the weighted Cohen's κ coefficient and the ICC(2,k) under a two-way random effects model. The results showed that all dimensions had κ values no lower than 0.74 and ICC values above 0.80, indicating a high level of agreement between raters (Landis & Koch, 1977; Koo & Li, 2016). To further assess the practical effect size of group differences, Cliff's δ was calculated based on the average scores of the two raters, and its 95% BCa confidence interval was estimated through 5,000 bootstrap resamples. The results indicated that the effect sizes for originality, analytical depth, structural coherence, and AI trace evidence all reached a very large level ($|\delta| = 1.00$), with AI trace evidence showing a negative effect, suggesting that low-income students exhibited significantly more AI traces than non-low-income students. The difference in disciplinary appropriateness was minimal ($\delta = -0.05$), indicating no significant group difference in this dimension. These analyses further enhance the robustness of statistical inferences under conditions of limited sample size (Tibshirani & Efron, 1993).

Phase 2: Qualitative content analysis

After the quantitative analysis, the research team randomly selected 9 students from each of the low-income and non-low-income groups, totaling 18 respondents, to conduct semi-structured in-depth interviews in June 2025. The selection followed a stratified purposive sampling approach to ensure balanced representation between the two socioeconomic groups while maintaining randomness within each stratum. The decision to include 18 participants was based on the principle of information saturation (Guest, Bunce & Johnson, 2006), where no new codes or themes emerged during the final interviews, indicating sufficient thematic depth and coverage. This sample size aligns with established recommendations for explanatory sequential mixed-methods research (Creswell & Clark, 2017), ensuring that the qualitative phase adequately captures the mechanisms underlying the quantitative differences identified in Phase I. All participants were anonymized using coded identifiers, with L1-L9 representing the low-income group and N1-N9 representing the non-low-income group. The interviews centered on the actual use process of AI writing tools, operational strategies, normative perceptions, experience of platform functions, writing motivation, and external support. Thematic Analysis was then used, following the six-step process proposed by Braun and Clarke (2006). Throughout the analysis, the team repeatedly referred back to the original transcripts to ensure the authenticity and representativeness of the identified themes.

Research results

Quantitative analysis results

As shown in Table 1, in the dimension of originality, the low-income group had a mean score of 1.46 (SD = 0.54), significantly lower than the non-low-income group's 4.38 (SD = 0.48). In terms of analytical depth, the low-income group's mean was 1.68 (SD = 0.43), compared to 4.24 (SD = 0.53) for the non-low-income group. For structural coherence, the means were 1.76 (SD = 0.52) and 4.32 (SD = 0.54), respectively, also showing a significant gap. In the AI trace dimension, the low-income group scored an average of 4.36 (SD = 0.60), while the non-low-income group scored 1.36 (SD = 0.51), reflecting a higher dependency on AI outputs and lower levels of post-editing among low-income students. The only dimension that did not show a significant difference between groups was disciplinary appropriateness, where the low-income group had a mean score of 3.54 (SD = 0.64), while the non-low-income group scored 3.46 (SD = 0.58), both demonstrating an above-average level of terminology use, suggesting comparable abilities between the two groups in this area. Table 2 presents the results of the Mann-Whitney U test. For originality, analytical depth, structural coherence, and AI trace, all U values were 0.0 with p-values less than .001, indicating that the differences were not only practically meaningful but also statistically highly significant. As for disciplinary appropriateness, U = 296.5 and p = .742, indicating no significant difference.

Table 1 Descriptive statistics of AI-assisted thesis writing by income group (n=50)

Dimension	Group	Mean	Std. deviation
Originality	Low-income	1.46	0.54
	Non-low-income	4.38	0.48
Analytical Depth	Low-income	1.68	0.43
	Non-low-income	4.24	0.53
AI Trace Evidence	Low-income	4.36	0.60
	Non-low-income	1.36	0.51
Structure Coherence	Low-income	1.76	0.52
	Non-low-income	4.32	0.54
Disciplinary Appropriateness	Low-income	3.54	0.64
	Non-low-income	3.46	0.58

Table 2 Mann-Whitney U test results for group differences

Dimension	U Statistic	p-value (Sig.)
Originality	0.0	<0.001 ***
Analytical Depth	0.0	<0.001 ***
AI Trace Evidence	0.0	<0.001 ***
Structure Coherence	0.0	<0.001 ***
Disciplinary Appropriateness	296.5	0.742 (n.s.)

Note: *** p < 0.001; n.s. = not significant.

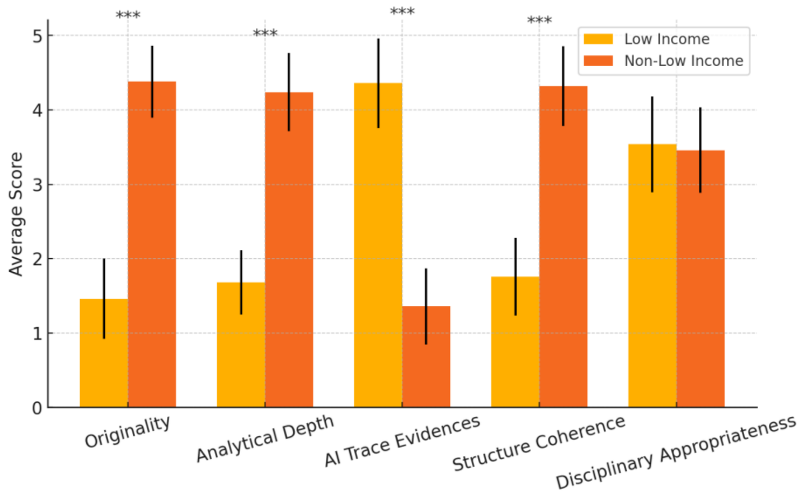

Figure 2 Bar chart of mean scores with 95 % CI

To more intuitively present the magnitude of score differences between the groups, a bar chart was plotted in Figure 2. In the first three dimensions, the average scores of the non-low-income group were approximately 2.5 to 3 times those of the low-income group, with the disparities clearly observable. The AI trace dimension displayed an inverse pattern, where the bars for the low-income group were substantially taller than those of the comparison group, indicating that more AI-generated features were retained in their theses. In the dimension of disciplinary appropriateness, the bar heights were similar and their 95% confidence intervals overlapped, further supporting the conclusion that there was no significant difference.

In summary, the quantitative analysis clearly revealed significant outcome disparities between low-income and non-low-income sports students in their writing practices using Gen AI tools. These differences centered on content quality and structural control rather than expertise reserves, suggesting that the current educational dividend of AI tools have not been equally distributed across different groups.

Qualitative analysis results

Writing pathways: One-step writing vs. Collaborative refinement

Two groups exhibited a clear divergence in their approaches to using AI writing tools, where students in the low-income group generally tended to adopt a one-shot generation strategy, with minimal post-editing or personalization of AI outputs. For example, one student remarked, "I just let it write an introduction and copied it directly, teachers cannot tell it is from AI anyway" (L7). In contrast, non-low-income students placed greater emphasis on iterative editing and content refinement, highlighting a collaborative human-computer writing process. As one student explained, "What AI generates is just a draft, I usually revise it several times to make the content better reflect my own thinking" (N4). This contrast reflects a difference in the depth of AI engagement and focus during the writing process: the low-income group was more task-oriented, while the non-low-income group emphasized process involvement and personal expression.

Information credibility: Trusting vs. Verifying AI-generated content

Different groups showed distinctly different attitudes toward the adoption and verification of AI-generated information, where low-income students generally showed a high level of trust in AI-generated content, and rarely actively verified or questioned its accuracy. For example, "I just thought that the AI must be right, it can write so smoothly, so it should be right" (L9). Non-low-income students, on the other hand, were more likely to check and screen the terms, data, and citations provided by the AI, as one student mentioned, "I am aware of AI hallucinations, so I usually double-check the data and references AI gives, just in case there are mistakes" (N7). This difference suggests that low-income students are relatively weak in information judgment and critical thinking and are prone to accept AI content unconditionally, whereas non-low-income students are more focused on the authenticity and reliability of the material.

Algorithmic register bias: Accepting vs. Adjusting specialized language

Interviews reveal that the official tone and cutting-edge terms produced by the AI affect the two groups of students in very different ways. For example, in the recommendations section the AI often suggests phrases such as "using wearable sensor devices," and several low-income students copy them straight into their theses, saying, "It sounds high-tech, my advisor will probably like it" (L1). A non-low-income student, however, noted, "The AI often slips in things that are unrealistic or come from other fields; they look reasonable at first, but they do not match reality, so I revise or simply delete them" (N6). This comparison shows that the model leans toward mainstream academic style and cross-disciplinary new terms, and students with less writing capital find it hard to tell and tend to accept the text as is, whereas more experienced students adapt it to the situation, partly offsetting the distortion caused by the model's register bias.

Platform engagement: Surface use vs. Resource-driven exploration

Clear differences also emerged in terms of AI platform usage levels and access to advanced features. Most low-income students relied solely on free versions of AI tools, had limited knowledge of premium features, and showed little willingness to explore them. One student remarked, "I just use the free one, as long as it works, there's no need to spend money" (L5). In contrast, many non-low-income students had experience subscribing to premium services and actively used advanced features on platforms like Doubao and ERNIE Bot to obtain longer texts, higher-quality outputs and citation support. One student noted, "I use the paid version of Doubao, which includes a deep learning model. It really cuts down the time I spend searching for sources. Totally worth it" (N1). This disparity not only reflects differences in financial capacity, but also affects the actual level of students utilizing AI to improve the efficiency and quality of their academic writing.

Writing motivation: Task completion vs. Skill development

n terms of writing motivation, two groups demonstrated differing orientations. Low-income students generally viewed the thesis as a mandatory task, using AI primarily to improve efficiency and get through it quickly. One student remarked, "It's just a graduation thesis, I'm just trying to get it done, I don't expect it to help me improve anything" (L2). While non-low-income students were more likely to see the writing process as an opportunity for self-improvement and skill demonstration, they actively used AI to enhance expression and structure. As one student explained, "I use AI mainly to make my writing smoother, but I still take responsibility for the final content. After all, it's also a way to train myself" (N8). This divergence in motivation directly influenced the depth of AI tool usage, and also reflected different psychological orientations and learning goals in response to academic demands.

Writing spervision: Unguided automation vs. Informed guidance

In the absence of consistent writing supervision, students demonstrated markedly different approaches to using AI tools. As the university has yet to establish formal instructional guidelines and some teachers remain unfamiliar with AI-assisted writing, many students were left to navigate the process on their own, resulting in some low-income students submitting AI-generated content directly as their final thesis without revisions, formatting, and academic standards. One low-income student said, "The university and teachers never explained how to use AI for writing. I figured it out myself, and if AI can write it, I just use it" (L3). Such unsupervised writing process reduces AI tools to mechanical generators, lacking the necessary critical review and refinement. In contrast, non-low-income students were more attentive to relevant technical information and proactively sought advice from teachers, thereby showing stronger awareness of formatting norms and higher capacity for post-editing. One student mentioned, "I ask teachers for tips, and some of them would remind me how to use AI in a way that aligns with academic integrity" (N2). These observations suggest that under uneven guidance structures, students' understanding and application of AI tools are becoming increasingly diverged, further widening the gap between institutional support and individual resource capacity.

Discussion

Differences in thesis writing quality

In terms of originality, theses written by low-income sports students tend to lack personalized expression. The content largely remains at the level of direct replication from AI-generated text, with little evidence of meaningful adaptation or reconstruction. This pattern supports Van Dijk's (2006) third-level digital divide theory, which argues that mere access to technological resources does not guarantee effective use or positive learning outcomes. Similarly, Yu et al. (2024) emphasize that the effectiveness of AI tool usage is closely tied to students' socioeconomic backgrounds, with those from higher socioeconomic groups more likely to convert technological access into meaningful academic outcomes. Interview data further reveal that low-income students often exhibit a high level of dependence on AI-generated content, lacking both the awareness and capability for content refinement and innovation, highlighting the limitations imposed by socioeconomic status on the ability to transform technological resources into educational achievements.

Regarding analytical depth, the theses produced by low-income sports students often exhibit superficial knowledge accumulation and descriptive content, lacking in-depth argumentation and critical thinking. Lobo (2023) found that under the compounded constraints of inadequate digital infrastructure, limited academic resources, and time pressure, undergraduate students majoring in sports disciplines generally encounter significant challenges in theoretical tasks such as academic writing and scientific reasoning, which in turn limits their performance in tasks requiring higher-order cognitive skills. This finding is further corroborated by interviews indicating that low-income sports students frequently treat AI-generated texts as final outputs rather than starting points, lacking the awareness and ability to engage in further analysis and critique. This pattern aligns with Bohnert and Gracia's (2023) observation that students from lower socioeconomic backgrounds are more likely to engage with digital technologies in a surface-level manner.

When examining structural coherence, the work of low-income sports students is often poorly organized, with weak logical flow and limited coherence between sections, reflecting a lack of effective structural composition skills. This phenomenon corresponds to what Scheerder et al. (2017) describe as a manifestation of the second-level digital divide, wherein insufficient technical skills hinder structured use and deeper creative engagement. In this study, low-income students frequently reported a lack of targeted guidance from instructors on how to use AI tools, highlighting that limitations in teacher competence and institutional support also serve as critical barriers in the process of translating technology into meaningful academic outcomes (Herold, 2017).

Differences in AI trace evidence further highlight the tendency of low-income sports students to directly adopt AI-generated content with minimal modification. As noted by Pyle and Andalibi (2021), the standardized language produced by AI tools is prone to direct use, and when students lack the capability to rework such content, their individual voice and originality are easily diminished. This issue is particularly pronounced among low-income students, whose constraints in time, energy, and resources often lead to a higher dependence on AI-generated outputs, thereby intensifying the visibility of AI traces in their work.

With regard to the disciplinary appropriateness, no significant differences were observed between the two groups, suggesting a certain degree of equity in resource distribution within this dimension. This may be attributed to the standardized curricular training system, which ensures relatively equal access to domain-specific knowledge. However, such equality in knowledge acquisition has not effectively translated into higher-level analytical and expressive capabilities, which aligns with Robeyns' (2005) interpretation of the Capability Approach, which emphasizes that equitable access to resources does not necessarily guarantee equitable conversion into functional capabilities.

Divergent roles of AI in academic writing

The quantitative and qualitative findings of this study reveal that the use of Gen AI writing tools yields highly differentiated outcomes across student populations, in particular, their empowering effects remain largely underutilized among low-income sports students. AI is perceived both as a convenient aid and, by many students, as a confusing and unmodifiable burden. This split in user experience highlights the divergent roles of AI writing tools in discussions of educational equity.

From a positive perspective, Gen AI is often seen as a democratizing technology. Yu et al. (2024) found in their large-scale data study that large language models can, to some extent, narrow the gap in expression between language-disadvantaged students and their peers. Addy et al. (2024) further pointed out that Gen AI tools have the potential to offer personalized feedback to underprivileged students and boost their writing confidence, but this benefit is often limited by the fact that AI is built on mainstream language norms and cultural frameworks. While AI can advance educational equity, it can also reinforce those same mainstream academic standards, creating cultural exclusion for marginal students, making it harder for those without writing cultural capital to revise and use AI-generated content. In interviews, low-income students reported that they "cannot understand AI content and so do not edit it," which illustrates the real inequality and cultural adaptation barriers hidden beneath the idea of technological neutrality.

Moreover, the effectiveness of technology use is also limited by external structural factors. Khowaja et al. (2024) introduced the SPADE framework, which highlights AI's potential risks in sustainability, privacy inequality, accessibility differences, and usage barriers. Although tools like Doubao and ERNIE Bot appear open, their advanced features often require paid subscriptions, excluding economically disadvantaged students. Rahmanipur and Mohammadi (2024) also noted that while AI can promote educational equity, without proper institutional support, cultural guidance, and practical training, its introduction may instead widen the digital divide and increase inequality in learning outcomes.

Robeyns (2005, 2006) and Litschka (2025) make clear within the Capability Approach framework that whether a technology empowers users does not depend on whether resources are available, but on individual's ability to turn them into meaningful action. In this study, non-low-income sports students were generally able to reorganize and adapt AI-generated content, whereas low-income students often copied it directly because they did not know how to revise or express ideas, effectively making AI a tool for others. This shows that empowerment and exclusion coexist and that technology's impact varies greatly across groups. As Chang (2020) argues, digital meritocracy has become a new breeding ground for inequality: under the banner of neutrality, technology reshapes educational advantages, advancing those who can handle it while silencing those on the margins. Therefore, we must look beyond the mere availability of AI tools and examine their real usability and effectiveness.

The reproduction of digital inequality through AI writing

This study found that Gen AI writing tools not only fail to bridge educational gaps in practice but also contribute to the reproduction of the digital divide through multiple mechanisms. This reproduction takes place at several levels, such as access, usage skills, algorithmic register bias, and educational support, resulting in a systemic structural imbalance.

First, in our sample both low-income and non-low-income sports students were able to log in to and use mainstream Gen AI tools, suggesting that the on-campus access gap has eased. At a wider regional and institutional level, though, infrastructure and cost barriers remain the main obstacles. The SPADE assessment by Khowaja et al. (2024) notes that access to Gen AI depends on stable networks and usage costs, which often keep disadvantaged groups from fully benefiting. Although access problems did not appear directly in our data, they may still influence real usage opportunities across different universities and areas.

Second, the gap in usage skills is the key driver of the divide's reproduction. Low-income sports students can reach AI but usually stop at simple keyword input and direct adoption, lacking the ability to reorganize, critique, and improve the output. Carter et al.'s (2020) AI divide model and the work of Jiang and Shao (2024) show that educational inequality has shifted from whether students can access AI to whether they can use it well. Our results confirm this view and show that, in four of the five AI transformation skills we valued, the gaps are sizable.

Third, algorithm bias and mainstream language norms add to structural inequality. Interviews show that many low-income sports students avoid editing AI output because they cannot follow the standard academic style. Although their program includes a fair amount of theory classes and a semester of thesis writing, students often spend most of their energy on field training. Coupled with limited writing support on campus, they have little practice with paper structure, citation rules, and academic tone, making it hard to build writing know-how. Pyle and Andalibi (2021) and Baker and Hawn (2022) note that large language models tend to produce mainstream academic wording, which does not match the limited writing experience of sports students and weakens their willingness to revise AI text. This mechanism still needs to be tested through corpus studies or teaching experiments.

Finally, teacher guidance and formal training are seen as key to improving AI literacy (Guizani et al., 2025; Herold, 2017), yet most low-income sports students in our interviews said they lacked concrete help on AI writing, and some teachers admitted they had little training themselves. This shortfall in support, combined with students' skill gaps, leads to clear differences in the effectiveness of AI tools among different groups.

Pathways for AI-assisted writing to advance common prosperity

As a core national strategy, common prosperity requires raising the overall level of education while closing group gaps to achieve true equality of opportunity and shared outcomes (Wang & Ruan, 2024). In the field of AI and education, this policy framework emphasizes inclusive digital transformation, balanced access to technological resources, and the cultivation of equitable AI literacy across social groups (Ministry of Education, 2025). However, the findings of this study reveal a structural tension between policy ideals and practical realities: without adequate institutional frameworks and capability-building mechanisms, Gen AI tools may unintentionally become new pathways for reproducing educational inequality. This misalignment highlights the need for targeted strategies that convert technological availability into genuine learning opportunities for all students. To unlock the potential of AI and promote educational equity, it is therefore necessary to design systematic interventions that address the multiple layers of the digital divide. We propose the following four directions:

To begin with, optimizing platform provision will guarantee fair access. The digital divide remains a structural barrier to common prosperity, and Zhang and Wang (2024) find that in underdeveloped regions, improvements in digital infrastructure bring especially high marginal benefits for education and income. The low-income sports students in this study are from areas with relatively limited resources, and their main bottleneck comes from the subscription fees for advanced LLMs. Khowaja et al. (2024) believe that cost barriers significantly limit disadvantaged groups' deep use of Gen AI. To address this obstacle, universities can centrally purchase institutional licenses for model services and deploy a campus-wide AI writing platform in libraries or on cloud desktops, allowing students to log in for free with their campus accounts to use writing, polishing, and translation modules. Centralized provision not only removes individual payment barriers but also embeds safety filters and learning resources to ensure output quality and academic integrity, turning infrastructure advantages into a practical starting point for equal development among disadvantaged students.

Moreover, we need to focus on capability conversion and AI literacy. Digital tools only turn into learning outcomes when used effectively (Robeyns, 2006). This study finds that low-income sports students generally lack the ability to edit, critique, and rebuild AI outputs, creating a structural dilemma of "having the tool but lacking the ability." To address this gap, AI literacy training should be embedded in existing thesis writing or research courses and supported through small workshops and peer tutoring, focusing on brainstorming, outline creation, language polishing, structure optimization, and bias recognition. Guizani et al. (2025) note that including human-machine collaboration skills and bias recognition in teaching helps maintain a dynamic balance between intelligent tools and fairness. With targeted training, disadvantaged students can move from mere tool use to effective application, thereby narrowing the ability gap.

Furthermore, we must refine institutional guidelines and build a supportive usage ecosystem. Interviews show that many students lack clear understanding of AI's availability and usage boundaries, falling into extremes of blind reliance or complete avoidance and revealing insufficient institutional support. Universities need to introduce clear guidelines for Gen AI use, specifying the range of allowed assistance and the boundaries of academic integrity, and establish feedback and review mechanisms. Elshaer et al. (2024) note that students' AI behaviors are shaped not only by how easy the tools are to use but also by disciplinary culture and social norms. Therefore, policy development must proceed alongside teacher guidance. Teachers can embed AI use into sports practice through case demonstrations and phased assignments, guiding students to develop critical judgment and appropriate usage strategies through hands-on practice.

Finally, we should promote human-machine collaborative teaching to activate capability conversion among disadvantaged students. AI can only promote equity when it becomes a real ability (Otto & Ziegler 2006). Lee and Lee (2021) point out that in physical education AI can provide personalized feedback and confidence support, and teachers should become strategic guides and psychological supporters. Based on this, we propose the "AI draft and teacher reinforcement" model: students first use AI to generate an initial draft, then teachers provide individual guidance on argument depth, logical structure and language accuracy, which both prevents blind reliance and improves writing quality. At the same time, student-led AI writing learning communities can be established, where senior or more technically proficient students share experiences and conduct peer reviews, promoting digital literacy flow within the group and helping low-income sports students overcome hierarchical barriers to achieve capability equity.

Conclusion

In light of the growing importance of the common prosperity strategy as a guiding value for education reform, Gen AI writing tools provide university students, especially those who have been traditionally disadvantaged in writing, with unprecedented learning support. However, this study, focusing on low-income sports students, found through quantitative and qualitative analysis that behind the appearance of equal tool availability, AI writing is quietly reproducing educational inequality. The results show that in originality, analytical depth, structure coherence, and AI trace evidence, low-income sports students fall far behind their non-low-income peers, revealing a systematic disadvantage in turning AI tools into high-quality academic work. Both groups showed similar performance in disciplinary appropriateness, indicating that the inequality does not stem from a lack of knowledge but from a breakdown in the process of converting tool use into real ability. This visible use yet invisible gap is the core risk highlighted by third-generation digital divide theory and the capability approach. Further analysis shows that the unequal effects of AI writing are not random errors in individual use but are driven by multiple structural mechanisms such as access conditions, usage skills, algorithmic register bias, and unbalanced educational support, all working together to reproduce inequality. Under current institutional arrangements and resource distributions, Gen AI can become a breeding ground for digital meritocracy, giving advantaged students greater learning leverage while trapping marginalized students in a cycle where more use leads to poorer outcomes.

Therefore, to achieve educational equity with the help of technology, we must move beyond the illusion that technology itself is the solution and focus on how to build real capacity through institutional design and educational practice. The four interventions proposed in this study explore a pathway from availability to usability to effectiveness. By following this pathway, Gen AI tools can benefit high-performing students and also support low-income students. Technology cannot guarantee fairness on its own, but we can use it to build fairness. This study emphasizes that true common prosperity is not an automatic byproduct of AI technology, but rather the result of an education system that consciously creates transformative conditions and opportunities for every student. Only then can education in the AI era drive efficiency while protecting justice, and open up possibilities without creating new forms of inequality.

Limitations and future research

While this study provides empirical insights into the mechanisms through which Gen AI may reproduce educational inequality among sports students, several limitations should be acknowledged. First, the data were collected from a single university and focused on a specific disciplinary group, which may restrict the generalizability of the findings to other institutional or disciplinary contexts. Second, income level was used as the primary socioeconomic indicator, while other potentially influential variables, such as gender, prior AI experience, academic performance, and institutional support were not fully examined. Third, the study adopted a cross-sectional design, therefore, it could not capture long-term changes in AI literacy development or capability transformation. Future research should address these gaps by incorporating a wider range of demographic and institutional variables, conducting multi-institutional or cross-regional comparisons, and exploring disciplinary differences between fields such as sports, STEM, and the humanities to examine how AI-mediated inequalities manifest across domains. Additionally, longitudinal or experimental approaches could be employed to trace the evolution of students' AI-related capabilities and to test the effectiveness of institutional interventions. Such studies would extend the present findings beyond a single context and contribute to a more comprehensive understanding of how generative AI can be harnessed to promote equitable education in China's digital era.

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Declaration of generative AI in scientific writing

The authors declare that no generative AI tools were used to generate or compose the scientific content of this manuscript.

CRediT author statement

Yi Dan contributed to the conceptualization, methodology, and manuscript writing. Chenfei Yang contributed to the data collection, formal analysis, and validation.

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