

Generative Artificial Intelligence and Inequalities in University Students' Employability: Socio-Technical Mechanisms, Structural Risks, and Educational Responses

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Abstract: Generative artificial intelligence is deeply involved in university students' career exploration, competency training, jobseeking expression, and careerrelated decisionmaking. Nevertheless, its popularization does not necessarily bring about equal distribution of employability gains. From a sociotechnical perspective, this paper situates employability inequality within the continuous interaction among technology, individuals, universities, and the labor market, and constructs an analytical framework of "structural resources — highquality access — affordance actualization — competency conversion — market recognition." The study reveals that generative artificial intelligence can lower the costs of careerrelated information and training services and thus produce opportunitycompensating effects. Meanwhile, it may generate cumulative advantages and disadvantages through stratified models and services, disparities in artificial intelligence literacy, uneven institutional support, careersignal inflation, and biases in algorithmic recruitment. Compared with the conventional digital divide, the generativeAIdriven employability divide is characterized by disparities in epistemic reliability, divergences in humanAI task orchestration, disjuncture between generated outputs and authentic competencies, as well as bilateral algorithmic interactions between jobseekers and recruiters. Accordingly, an inclusive humanAI collaboration mechanism should be built at three levels: students' critical artificialintelligence employability literacy, universities' competencyconversion systems, and transparent and accountable technology and recruitment governance.

Keywords: Generative artificial intelligence; University students' employability; Sociotechnical systems; Career signaling; Algorithmic recruitment

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1. Introduction

Generative artificial intelligence is rapidly permeating university students' learning, career exploration,

competency training, and jobhunting preparation. Compared with traditional search engines and standardized onlinelearning tools, it enables information integration, content generation, scenario simulation, and realtime feedback via naturallanguage interaction, and delivers relatively personalized career advice ^[1-2]. It further transforms career guidance from periodic, standardized services toward continuous, personalized humanAI collaboration ^[3]. Such tools reduce the marginal costs of jobinformation analysis, skill practice, résumé revision, and interview training. They provide lowcost, repeatable employment support for students who lack careerrelated information, jobhunting experience, or individualized guidance, and may therefore yield opportunitycompensating effects ^[4].

However, formal technological popularization does not equal substantive equality in employment benefits. Artificialintelligence tools can be deployed to expand information sources, verify understandings, and train learners for complex tasks; alternatively, they may be used to generate ready-made answers, replace learning procedures, and produce standardized jobapplication materials ^[5]. The ultimate benefits students obtain hinge on model quality, domainspecific knowledge, artificialintelligence literacy, teacher guidance, curriculum design, practical opportunities, and recruitment rules. Generative artificial intelligence hence carries dual potentials for empowerment and stratification: while it lowers the threshold for accessing career support, it may interact with preexisting disparities in economic, educational, and social capital to form new employability divides ^[4].

Employability cannot be equated with résumé quality, jobhunting techniques, or final employment outcomes. Instead, it encompasses the knowledge, skills, professional identity, adaptability, and social resources that students need to enter the labor market and cope with occupational changes ^[6-9]. These resources can be converted into employment opportunities only after going through competency formation, competency conversion, careersignal construction, and market recognition. Generative artificial intelligence may improve tangible outputs, yet it does not automatically foster disciplinary comprehension, independent judgment, or competency transfer. Even when students have developed authentic competencies, those competencies may fail to receive fair recognition from recruitment systems.

Existing research has investigated generativeAI educational applications, the digital divide, graduate employability, and algorithmic recruitment, respectively. Digitaldivide scholarship has expanded its focus from device access toward skills and outcome disparities ^[10]. Studies on algorithmic recruitment have uncovered biases, fairness deficits, and transparency problems in automated screening ^[11-13]. Even so, extant literature cannot fully explain emerging phenomena such as the disjuncture between algorithmgenerated outputs and realworld competencies, homogenization of career signals, and simultaneous algorithmization on both the jobseeker and recruiter sides. Against this backdrop, this paper adopts a sociotechnical lens to build the analytical framework of “structural resources — highquality access — affordance actualization — competency conversion — market recognition.” It analyses how generative artificial intelligence reshapes university students’ employability, and how technology, individuals, universities and the labor market jointly produce new forms of inequality.

2. Theoretical foundations and analytical framework

Employability refers not merely to knowledge, skills and psychosocial resources held by individuals, but also to the processes through which those resources are formed, presented and recognized within educational and labormarket contexts ^[6-9, 14]. This paper identifies four sequential links: first, competency formation, in which students develop disciplinary expertise, transferable skills and professional identity through coursework, practice, career exploration and reflection ^[7, 15]; second, competency conversion, through which information, texts and feedback provided by artificial intelligence are internalized into authentic, transferable

competencies for independent deployment; third, career signal construction, where students demonstrate their competencies to employers via academic credentials, projects, internships, portfolios, résumés and interviews^[16]; fourth, market recognition, in which recruitment platforms, algorithmic systems and organizational evaluators screen and interpret such signals.

Technological affordances denote action possibilities available for actors within given contexts, rather than simple aggregations of technical functions^[17]. Generative artificial intelligence can lower entry level costs for understanding career related information and self expression, and deliver scenario simulation, personalized recommendations, and instant feedback^[1]. Still, it is constrained by misinformation, opaque sources, ethical risks, and overreliance^[2]. Its effectiveness depends heavily on students' prior knowledge and usage patterns. Students with solid disciplinary foundations are better positioned to formulate high quality prompts, detect errors, and revise outputs. By contrast, students with weak foundations tend to mistake linguistic fluency for factual validity.

From a sociotechnical perspective, technological outcomes are not determined solely by technical attributes. They emerge from the interplay of human agency, material properties of technology, and organizational practices^[17–18]. Structural resources shape which models, specialized datasets, and guidance support are accessible to students. Artificial intelligence literacy together with domain knowledge determines whether students adopt enhancement oriented or substitution oriented usage modes. University curricula, teacher scaffolding, authentic assessment, and practical platforms govern whether AI generated content can be translated into genuine competencies. Career signal configurations and recruitment algorithms further decide whether competencies can be turned into job opportunities. Employment opportunities in turn reshape practical experience, social capital, and subsequent technological resources, creating cumulative feedback loops.

The core argument of this framework is not whether generative artificial intelligence delivers universal benefits, but under what resource conditions, institutional arrangements, and market rules its affordances can be actualized by different student groups. Distinguishing formal access, practical usage, competency internalization, and market recognition prevents researchers from conflating tool adoption rates with improved employability, and avoids attributing structural inequalities exclusively to individual student effort.

3. The reconstruction of university students' employability by generative artificial intelligence

First, career exploration shifts from information searching toward algorithm mediated inquiry. Generative artificial intelligence integrates job responsibilities, competency requirements, and industry trends, and organizes fragmented information into coherent career interpretations. It particularly helps students without industry connections or those pursuing cross disciplinary careers reduce cognitive barriers. Nevertheless, its outputs may contain outdated facts and factual mistakes, and are shaped by training datasets and dominant career narratives^[2]. Models do not merely transmit information; they frame students' understanding of the occupational world via categorization, comparative dimensions, and recommended pathways. The validity of algorithm assisted career exploration hinges on students' capacity to cross check generated content against corporate materials, industry documents, teacher advice, and hands on practical experience.

Second, competency development evolves from standardized training toward human AI collaboration. Generative artificial intelligence decomposes occupational competencies, generates practice tasks, simulates workplace scenarios, and delivers immediate feedback^[1]. While using such tools, students must define

problems, supply contextual background, compare alternatives, verify outputs, and take responsibility for final judgments. HumanAI task orchestration itself becomes a new competency for digital-era workplaces. High-quality algorithm-generated outputs, however, do not equate to authentic competencies. When students produce reports with AI assistance, they may still lack the ability to explain or transfer relevant knowledge independently^[5]. Enhancement-oriented usage treats artificial intelligence as a cognitive scaffold; substitution-oriented usage replaces core cognitive activities with ready-made outputs and readily causes disjuncture between external deliverables and internal competencies^[2, 5].

Third, career signal construction transforms from individual self-presentation to AI-aided representation. Generative artificial intelligence supports students in extracting personal experiences, matching qualifications with job criteria, polishing résumés, and conducting mock interviews, offering compensatory value for students with limited writing experience and insufficient professional guidance. When large numbers of applicants employ similar models and templates, textual career signals become highly homogenized. Drawing on signaling theory, it can be inferred that linguistic features that once reflected communication competence, job hunting efforts, and occupational insight turn into low-cost standard features, lowering their discriminative validity^[16]. Employers consequently attach greater weight to verifiable signals such as authentic projects, internship experience, work samples, and professional certificates, allowing advantages rooted in educational resources and social capital to resurface.

Fourth, career transition moves from experience-based decision-making to human-AI collaborative judgment. Generative artificial intelligence synthesizes personal backgrounds, career aspirations, and practical constraints, compares alternative pathways, and breaks long-term objectives into actionable steps. Yet career decisions involve values, identity, family obligations, and risk tolerance, which cannot be fully standardized into data. Model-imposed categorizations may produce framing effects; submitting private information for personalized recommendations also raises data-privacy risks. Therefore, generative artificial intelligence should function as a decision-support instrument rather than a substitute for value-based judgment and personal accountability.

4. Sociotechnical mechanisms behind employability inequality

4.1. Inequality in high-quality access

The access divide concerning generative artificial intelligence goes beyond the binary question of “whether one can use AI.” It manifests as stratification in model performance, functional tiers, continuity of usage, specialized resources, and supporting ecosystems. Students from economically advantaged backgrounds are more likely to consistently access high-performance models, specialized databases, and multi-source verification tools. Students with fewer resources face constraints on usage quotas, document-processing limits, and real-time information updates. Existing disparities in graduate employability across different university types are further reproduced under generative-AI contexts through gaps in platform procurement, curriculum embedding, faculty readiness, and allocation of specialized resources^[14].

4.2. Disparities in artificial intelligence literacy and affordance actualization

Artificial intelligence literacy covers not only operational proficiency but also comprehension, application, evaluation, and ethical reasoning^[19]. Within employability-development contexts, it additionally includes task analysis, human-AI labor division, content verification, and processor-oriented reflection^[20]. Students with

higher literacy and solid domain knowledge tend to adopt enhancement-oriented usage, whereas less-literate students tend to accept complete algorithm-generated outputs uncritically. Such gaps cannot be reduced to individual deficits. Outcome-focused assessment, low-value assignments, and heavy time pressure also incentivize substitution-oriented behavior. Domain knowledge and AI literacy are mutually complementary: learners with stronger subject expertise can better assess output quality and reap greater benefits from artificial intelligence. Paradoxically, students who need technological support the most often lack the disciplinary knowledge required to validate AI outputs.

4.3. Institutional support gaps and divergent competency conversion

Generative artificial intelligence provides potential competency resources, yet their conversion hinges on university institutions^[18]. Curriculum design defines application scenarios for AI tools; teacher guidance shapes how students interpret and revise generated outputs; assessment modes determine whether students prioritize processes or final deliverables; practical platforms test whether algorithm-designed solutions work in real-world contexts. Well-resourced universities integrate generative artificial intelligence into disciplinary coursework, authentic projects, and university-industry cooperation, converting AI outputs into professional competencies and occupational experience. By contrast, if AI education is confined to introductory tool workshops and assessment centers on finished written texts, algorithm-produced content may be misattributed to student competencies. Family background and social capital further determine whether students can translate AI-formulated plans into internships, projects, and professional networks^[9].

4.4. Career signal inflation and algorithmic recognition

Generative artificial intelligence lowers production costs for job-application texts and weakens the correspondence between textual signals and authentic competencies. According to signaling-theory logic, when recruiters struggle to differentiate candidates via résumés and interview narratives, they may introduce work-sample tests, onsite assessments, and background checks, or raise the weighting of high-cost verifiable signals^[16]. This may reinforce advantages associated with institutional prestige and internship resources while increasing overall job-search burdens.

Meanwhile, employers widely deploy algorithms for résumé screening, candidate ranking, and job matching^[11]. Models trained on historical hiring and performance records tend to reproduce group disparities and evaluative preferences embedded in past recruitment practices, translating algorithmic biases into disadvantageous treatment for certain groups^[12–13, 21]. Even without explicit sensitive-attribute inputs, proxies such as educational trajectories and geographic locations may trigger discriminatory outcomes^[12, 22]. Algorithmic opacity prevents jobseekers from understanding or appealing against rejection decisions^[11]. This paper proposes the concept of bilateral algorithmic interaction: jobseekers adapt résumé keywords and formats using generative artificial intelligence, while employers strengthen detection, verification, and screening procedures. Recruitment competition is partially transformed into competition over adaptation to platform rules.

The abovementioned mechanisms create cumulative feedback loops: high-quality access increases the likelihood of enhancement-oriented usage; institutional support facilitates authentic competency building; genuine competencies together with credible career signals improve access to internships and jobs, which in turn foster richer occupational experience, social capital and technological resources^[9]. Conversely, low-quality access, substitution-oriented usage, failed competency conversion, and market exclusion produce cumulative disadvantage. These loops are not an inevitable outcome of technological progress. Compensatory

resource allocation, teacher scaffolding, authentic assessment, practical opportunities, algorithmic auditing, and human review can interrupt adverse cascades.

5. Educational and institutional responses

At the individual student level, emphasis should shift from technical proficiency toward critical humanAI collaboration integrating comprehension, evaluation, application, and ethical deliberation^[19–20]. Critical artificialintelligence employability literacy encompasses identifying taskrelated risks, allocating responsibilities between humans and artificial intelligence, verifying generated content, promoting competency transfer, safeguarding careersignal authenticity, and protecting personal privacy. Students may leverage artificial intelligence for information synthesis and linguistic revision, but human agents must retain final accountability for professional judgments, validation of reallife experience, and major careerrelated decisions.

Universities ought to guarantee equitable access to highquality tools, specialized databases, and necessary hardware, and deliver compensatory support for students suffering financial hardship, limited digital skills, or insufficient social support. Artificialintelligence employability literacy should be embedded within disciplinary curricula, careerplanning programs, and practical teaching^[20]. Course design should connect to subjectspecific tasks and ethical risks instead of offering generic tooltraining modules^[18]. Assessment should move beyond evaluating final written deliverables and adopt authentic projects, work samples, oral defenses, process logs, and reflective reports to distinguish AIgenerated content from genuine student competencies^[3]. Furthermore, universities should connect coursework, practical training, and careerservice systems. Through authentic projects, universityindustry collaboration, industry mentors, and career portfolios, knowledge acquired with AI support can be transformed into verifiable professional outcomes.

Technology platforms and employers need to pursue transparency and accountability. Platforms shall clarify information sources, applicable contexts, and data-usage rules for career advice and job recommendations, and grant users rights to modify, correct, and delete personal data. Employers should treat algorithms merely as auxiliary instruments and must not rely solely on algorithmic outputs to reject applicants or make final hiring decisions^[11, 13]. Algorithmicimpact assessments shall examine pass rates, error rates, and fairness performance across different demographic groups, auditing proxy variables, prediction targets, and biases inherited from historical datasets^[12–13, 21]. Substantial human review, explanation, and appeal channels should be established for consequential automated recruitment decisions^[11, 13, 22].

6. Discussion and conclusion

This paper conceptualizes generativeAIdriven employability inequality as a continuous process spanning competency formation, competency conversion, careersignal construction, and market recognition. Its theoretical contributions are threefold. First, it redefines employability: rather than viewing it as stable individual attributes, this study frames employability as relational capacities that require validation by educational institutions and the labor market^[8–9]. Second, it integrates both compensating effects and amplifying stratification effects within one unified analytical framework^[4–5]. Third, compared with the traditional digital divide, the newform employability divide exhibits prominent epistemic, agent-centered, and dynamic features, including stratified highquality access, divergences in humanAI task orchestration, disjuncture between algorithmgenerated outputs and authentic competencies, and bilateral algorithmic interactions between jobseekers and recruiters. This paper

does not conclude that technology necessarily widens gaps. Instead, compensating and amplifying effects may covary across tasks, student groups, and developmental phases, contingent on how technological resources and institutional obligations are distributed.

The arguments presented carry clear boundary conditions. Generative artificial intelligence is more likely to yield compensating benefits for wellstructured tasks with verifiable outcomes. Tasks drawing on tacit knowledge, complex interpersonal relations and valueladen judgments depend heavily on disciplinary expertise and human support. Disciplinary backgrounds, university resources, student developmental stages and labor market institutions moderate the strength of the mechanisms uncovered ^[14–15]. Future research may deploy questionnaires, interviews, experiments and longitudinal tracking to test correlations among access quality, usage patterns, university support, career signaling and algorithmic recognition.

Overall, the educational value of generative artificial intelligence lies not in enabling students to delegate more tasks to machines, but in expanding access to information, training, practical experience and career support for students from diverse resource backgrounds. Only by ensuring equitable access, critical usage, authentic competency conversion and transparent market recognition can technological efficiency be translated into more inclusive career development opportunities. Universities, technology platforms and employers should move beyond mere tool provision toward collaborative governance. Generative artificial intelligence should serve as a public resource fostering graduate employability, rather than becoming a new stratification mechanism that reproduces preexisting educational and employment disparities.

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