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Mitigation of College Students' Employment Friction and Adverse Selection Risk under the Intervention of Large Language Models: A Mechanism Analysis from the Perspective of Routine-Biased Technological Change

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Abstract: *Routine-biased technological change (RBTC) has profoundly restructured the skill premium structure of the labor market, drastically compressed the living space of routine jobs, and thus exposed the structural lag of the traditional college employment guidance system in implicit competency mapping. This paper aims to deconstruct the dual mechanism of large language models (LLMs) in the micro-level employment intervention process. By comparing with the traditional static tutoring model, the study points out that LLMs, relying on their unstructured feature extraction capability, have effectively broken through the job search information barriers of job seekers and realized the paradigm shift from "typesetting polishing" to "dynamic semantic mapping". However, in practical application scenarios, the underlying alignment mechanism and text generation logic of algorithms can easily strip job seekers of their real practical baselines, inducing the risks of "ability falsification" and Akerlof's adverse selection in the labor market. To this end, this paper proposes that a high-fidelity dynamic game confrontation mechanism must be introduced into the intelligent empowerment framework, and the negative backlash of text "overstepping reconstruction" should be blocked through cognitive load limit testing, so as to provide a theoretical framework for the development of intelligent employment assistance systems with anti-reverse dependence attributes.*

Keywords: *Large language models, Routine-biased technological change, Semantic reconstruction, Adverse selection, Dynamic game*

1. Introduction

The industrial transformation centered on artificial intelligence is fundamentally reshaping the supply-demand balance between the macro labor market and the micro employment guidance system. At present, college graduates in China generally face the practical dilemma of insufficient job information collection ability and inadequate comprehensive employment preparation when conducting job searches[1]. This lag on the supply side has generated intense structural friction with the intelligent transformation of the macro industrial structure.

On the one hand, the widespread penetration of artificial intelligence technology has triggered the polarization effect of the labor market. Intelligent algorithms have not only massively cut routine and repetitive jobs, but also significantly expanded the demand for "non-routine cognitive" jobs (such as cross-border analysis and unstructured communication) through the productivity effect[2]. On the other hand, the traditional employment guidance model lacks high-fidelity practical training scenarios and accurate data mapping capabilities, making it difficult for graduates to transform fragmented campus experiences into a composite competency spectrum that meets the needs of the intelligent industry. Against this background, large language models (LLMs), as a general-purpose technology (GPT), have formally intervened in the micro-level employment intervention process. This paper intends to clarify the intervention boundaries of large models in resume semantic reconstruction and interview dynamic games through mechanism deduction, so as to avoid the distortion of labor market signals caused by technology abuse.

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2. Theoretical Foundation: RBTC Impact and Micro Employment Friction

The prerequisite for accurately positioning the intervention path of large language models is to clarify the underlying reconstruction logic of artificial intelligence on labor skill demands.

2.1. Routine-Biased Technological Change and Demand Polarization

At present, the academic community generally adopts the routine-biased technological change (RBTC) paradigm to analyze the unbalanced impact of artificial intelligence on the employment structure. The reconstruction of the labor market by technological progress is not a simple overall substitution, but a structural stripping based on the attributes of job tasks. Intelligent machines and automated algorithms mainly replace rule-based and procedural routine manual and routine cognitive labor[3]. Meanwhile, empirical data show that the improvement of enterprises' artificial intelligence technology level has produced significant complementary and spillover effects on "non-routine cognitive" jobs that require high professional knowledge, critical thinking and complex communication skills[2]. The screening criteria of the labor market have comprehensively shifted from explicit professional knowledge reserves to implicit complex problem-solving abilities.

2.2. Supply-side Lag: Structural Disconnection of the Traditional Employment System

Faced with the external impact of demand polarization, the supply side of college students' employment shows serious stickiness and lag. Restricted by the single professional training model, some college graduates lack interdisciplinary knowledge backgrounds and comprehensive human-machine collaboration qualities, and their existing competency structures are seriously mismatched with the urgent demand of the intelligent industry for interdisciplinary talents[4]. In addition, the employment guidance of traditional colleges and universities is highly dependent on the empirical inference of guidance staff, with scattered and inefficient information matching channels. This structural friction of "high cognitive demand vs. low transformation capacity" constitutes the realistic motivation for introducing large language models to carry out high-dimensional semantic intervention.

3. Resume Reconstruction: Dynamic Semantic Mapping and "Lemon Market" Risk

The essence of large language models in the resume optimization link is to eliminate information asymmetry between supply and demand, but their technical characteristics also simultaneously introduce the systemic risk of ability signal distortion.

3.1. From Static Polishing to Unstructured Feature Extraction

Resume modification under the traditional mechanism only stays at the superficial level of vocabulary replacement and format adjustment, and cannot touch the logical reconstruction at the bottom of competency. The intervention of large language models has triggered a paradigm shift in this link. Relying on its powerful natural language processing (NLP) capability, the algorithm can parse massive unstructured recruitment texts in seconds and accurately extract the core features of "non-routine work" for specific positions (especially emerging digital occupations)[2]. Based on this feature vector, the large model reversely guides job seekers to tap into their campus experiences, and forces the originally invisible implicit human capital into a high-density competency map identifiable by the labor market.

3.2. Ability Falsification and Adverse Selection Induced by Algorithmic Alignment

Excessive empowerment of technology is often accompanied by the collapse of the signaling mechanism. The underlying alignment mechanism of LLMs tends to generate logically perfect and structurally homogeneous grand narratives. When the logical density of the text generated by the model exceeds the actual practical baseline of job seekers, technological empowerment degenerates into "ability falsification". In the absence of objective verification, such inflated text signals will flatten the real ability variance of individuals, increase the screening cost on the enterprise side, and then trigger the "lemon market" effect similar to that under Akerlof's framework—bad ability signals driving out good ones, which will eventually lead to a trust crisis in the micro labor market.

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4. Mechanism Comparison Between Traditional and Intelligent Employment Intervention Models

To intuitively analyze the efficacy differences and potential threats before and after the intervention of large language models, this paper constructs a cross-dimensional mechanism comparison matrix (see Table 1).

Table 1: Cross-dimensional Comparison Between Traditional Intervention Mechanism and LLM Empowerment Mechanism

Evaluation Dimension	**Traditional Employment Intervention Mechanism**	**LLM-empowered Intelligent Intervention Mechanism**	**Core Implications & Risk Reminders**
Core Mechanism	Empirical inference based on tutors' individual experience	Dynamic semantic mapping based on unstructured feature extraction	LLM reduces information friction but introduces signal distortion risk
Information Processing Capability	Manual extraction of job requirements, low efficiency and subjective bias	Second-level parsing of massive recruitment texts, micro-fitting of supply and demand features	Significantly lowers job search costs but may flatten individual competency variance
Competency Explicitation Path	Static vocabulary replacement and typesetting adjustment	Heuristic multi-round interaction to reconstruct STAR structure	The boundary is "mining" rather than "fabricating"; must be anchored to verifiable baselines
Interaction Depth	Linear matching based on fixed scripts, no contextual follow-up	Multi-round contextual memory, dynamic pressure testing for logical loopholes	Breaks rote-based interview strategies but depends on industry corpus quality
Assessment Focus	Memorization accuracy of professional knowledge	Creative thinking, complex problem-solving and emotional intelligence	Aligns with RBTC-driven labor market demand but may cause technological dependence
Risk Control Mechanism	Manual review by tutors, low coverage and inconsistent standards	Parameter constraint matrix + closed-loop "text generation-practical verification"	Dynamic game mechanism is the core to block "overstepping reconstruction"

5. Interview Game: The Practical Backlash of Dynamic Confrontation Against "Overstepping Reconstruction"

The only way to block the risk of ability falsification generated in the resume optimization stage is to introduce a high-fidelity dynamic game mechanism in the interview link to form a logical closed loop of "text generation-practical verification".

5.1. Non-linear Game Breaking Through Linear Decision-Making

Emerging jobs created by artificial intelligence technology highly depend on employees' real-time communication and adaptability in complex and changeable human-machine collaboration environments[4]. Traditional interview simulations based on fixed question banks are completely unable to transmit the high-pressure attribute of the real workplace. The confrontation system driven by large language models has broken the static decision tree logic and evolved into a dynamic game system with strong contextual memory. Virtual interviewers can implement precise logical disassembly and extreme pressure testing on the weak links and grand narratives in job seekers' resumes.

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5.2. Cognitive Load Limit Testing and Parameter Constraints

When job seekers use algorithms to unauthorizedly generate distorted resumes, their actual cognitive load cannot support the logical structure in the texts under the high-frequency and intensive questioning by LLMs, and they will inevitably face a systematic evaluation collapse. This practical backlash mechanism effectively curbs the impulse of "overstepping reconstruction" at the front end. Therefore, future intelligent intervention models must embed a strict parameter constraint matrix, which mandatorily specifies the boundaries of text generation and ensures that the final output is strictly anchored to the verifiable academic and practical baselines of job seekers.

6. Conclusions

Large language models are not mere polishing tools in micro-level employment intervention, but core variables that reshape the supply-demand matching signals in the labor market. The study shows that under the external impact of routine-biased technological change, LLMs can effectively break through information barriers and transform implicit human capital into explicit features; however, their underlying logic can easily trigger the adverse selection risks of text homogenization and ability falsification. Future academic exploration and system development must abandon one-sided technological optimism and strive to build a closed-loop testing system including "baseline mapping, dynamic confrontation, and parameter constraints". Only by strictly limiting large models within the "catalyst" boundary of auxiliary decision-making can we effectively improve the real employment competitiveness of graduates.

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