Vol.7 Iss.3 2026 Communication & Education Review
https://doi.org/10.37420/j.cer.2026.042

# Mechanisms and Pathways for Empowering University Career Guidance through AI Agents in a Human-Machine Collaboration Context: An Empirical Study Based on TPC Theory

**Lu Lejun***
**Guangdong University of Finance, Guangdong, China**
***Corresponding author, E-mail: b159@gduf.edu.cn**

## Abstract

*With the rapid advancement of generative artificial intelligence, the use of AI agents to address the long-standing mismatch between supply and demand in university career guidance has become increasingly feasible. This study examines four types of AI-based career guidance agents—resume optimization, interview training, career planning, and psychological counseling—implemented in the School of Accounting at a Chinese university. Grounded in Task–Performance Chain (TPC) theory, which integrates the core logic of task–technology fit, this research adopts a mixed-methods approach combining questionnaire surveys and in-depth interviews. A total of 207 graduating students were surveyed to systematically analyze their user experiences and feedback. The findings reveal that the empowering effects of AI agents in career guidance are not evenly distributed but instead exhibit a pronounced pattern of "asymmetric empowerment." Specifically, in highly standardized tasks such as resume optimization, AI agents function through an "efficiency substitution mechanism" based on rule-driven automation. In semi-structured tasks such as interview training, they operate through a "capability enhancement mechanism" enabled by scenario-based simulations. In contrast, in low-structured tasks such as psychological counseling, a "trust inhibition mechanism" emerges due to limitations in emotional engagement. Consistent with prior research, the distinction between "instrumental trust" and "relational trust" appears to be a critical factor influencing students' willingness to adopt AI agents, a conclusion further supported by the empirical data of this study. Based on these findings, this paper proposes the construction of a "tiered and differentiated" human–machine collaborative ecosystem. It also redefines the role of career counselors as both "human–machine interface coordinators" and "gatekeepers of emotional value." These insights provide both theoretical contributions and practical implications for the digital transformation of university career guidance.*

## Keywords

*generative artificial intelligence; educational agents; career guidance; task–performance chain; human–machine collaboration; digital competence*

© 2026 by the author(s); licensee Mason Publish Group, this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (http://creativecommons.org/licenses/by/4.0/)

# 1. Introduction

Amid the dual forces of the massification of higher education and the digital–intelligent transformation of society, university career guidance is facing increasingly significant challenges. The sustained growth in the number of graduates, coupled with the rising demand for personalized services, has placed considerable pressure on university counselors, who are often constrained by high student-to-staff ratios and burdensome administrative tasks. As a result, service provision tends to rely on broad, undifferentiated approaches rather than delivering precise, individualized support. The rapid rise of generative artificial intelligence (AIGC) offers a powerful technological lever to address this long-standing dilemma. Large Language Models (LLMs) [1], as the core technology underpinning AIGC, can be broadly categorized into general-purpose LLMs and domain-specific LLMs based on their task-processing capabilities. General-purpose LLMs are capable of handling a wide range of language understanding tasks, whereas domain-specific LLMs are trained on extensive corpora of specialized texts to better serve particular industries [2]. In tasks requiring domain knowledge, specialized terminology, and analytical depth, domain-specific LLMs typically outperform their general-purpose counterparts [3]. By leveraging large-scale domain-specific data and targeted training on foundational models, vertical LLMs acquire the ability to understand contextual nuances, generate personalized content, and even simulate human roles, thereby offering more effective support for specific sectors. Deploying such domain-specific AI agents in university career guidance enables the systematic integration and optimization of learning elements and processes. This facilitates the redesign of learning workflows, supports learner-centered customization, and enables in-depth analysis and tailored planning. Consequently, it promotes the development of more personalized, precise, and scalable learning systems [4]. In practice, these technologies can support students in personalized learning, intelligent Q&A, and learning analytics, while also relieving counselors from repetitive tasks such as resume editing and routine inquiries, allowing them to focus more on high-value, in-depth mentoring.

However, the introduction and application of technology is not a linear or seamless process. In the pilot implementation of this study, a noteworthy phenomenon emerged: four AI-driven career guidance agents—resume optimization, interview training, career planning, and psychological counseling—built upon the same technological foundation exhibited markedly different levels of effectiveness. This observation gives rise to the central research question of this study: in real-world career guidance contexts, how do task characteristics define the boundaries of AI agent applicability? Furthermore, how does task–technology fit influence ultimate employment outcomes through students' usage behaviors? To address these questions, this study adopts the Task–Performance Chain (TPC) framework as its analytical lens, introducing "task standardization" as a key antecedent variable. The aim is to uncover the differentiated mechanisms underlying technological empowerment and to explore a new paradigm of human–machine collaboration that integrates technological efficiency with humanistic care.

# 2. Research Design

This study adopts the School of Accounting at a university as its case study. In May 2025, the school introduced four AI-based career guidance agents for graduating students, including a resume optimization agent, an AI interview agent, a career planning agent, and a psychological counseling agent. The study pe-

© 2026 by the author(s); licensee Mason Publish Group, this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (http://creativecommons.org/licenses/by/4.0/)

riod spans the peak season of the autumn recruitment cycle. A mixed-methods approach was employed for empirical analysis. First, a questionnaire survey was administered to 220 graduating students, yielding 207 valid responses. The analysis identifies differences among the four AI agents in terms of usage rate, perceived capability enhancement, and user evaluation, which are treated as key mediating variables within the TPC. Subsequently, in-depth interviews were conducted with 10 representative users to provide qualitative insights, aiming to uncover the underlying psychological motivations and deeper mechanisms behind the observed data patterns. It should be noted that the sample is primarily drawn from finance- and economics-related majors; therefore, the generalizability of the findings requires further validation.

## 3. Research Findings

Empirical evidence indicates that the empowering effects of AI agents are not universal. Instead, as the level of task standardization decreases, three distinct mechanisms of empowerment emerge. All three mechanisms operate through the transmission process described by TPC theory.

### *3.1 Mechanism I: "Efficiency Substitution" in Highly Standardized Tasks*

This mechanism is most applicable to highly standardized tasks with clearly defined rules, such as resume optimization. Prior research suggests that such tasks are characterized by explicit operational procedures and evaluation criteria, making it easier to achieve a high degree of alignment between technological tools and task requirements. The findings of this study provide empirical support for this claim. From a data perspective, the resume optimization agent demonstrates a pattern of "high coverage, high evaluation, rapid workflow, and deep usage." Among the 207 respondents, 169 students (81.6%) reported using the resume optimization function. Prior to using the AI tool, students' self-assessed ability in resume writing and optimization had a mean score of 6.125 (SD = 1.23), indicating a moderate overall level of competence. After using the AI tool, the average score increased to 8.788 (SD = 1.05), with a reduced standard deviation. This suggests not only a significant overall improvement in students' abilities but also a reduction in variability across individuals, indicating a more consistent level of competence following tool usage.

*Table 1. Descriptive Statistics of Students' Resume Competency Scores Before and After Using AI*

| Indicator | Before Use (Pre-Intervention) | After Use (Post-Intervention) | Difference (Post-Pre) |
|---|---|---|---|
| Sample Size (n) | 169 | 169 | 169 |
| Mean (M) | 6.125 | 8.788 | 2.663 |
| Standard Deviation (SD) | 1.23 | 1.05 | 0.89 |
| Minimum | 3 | 6 | 1.5 |
| Maximum | 8.5 | 10 | 4 |

Students' competency scores after using the resume AI were significantly higher than those before use,

© 2026 by the author(s); licensee Mason Publish Group, this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (http://creativecommons.org/licenses/by/4.0/)

$t(168) = 18.62$, $p < 0.001$. Further analysis yielded a large effect size (Cohen's $d = 2.15$), with an average improvement of 2.663 points on a 10-point scale. These results indicate that the use of the resume optimization agent substantially enhances students' abilities in resume writing and refinement.

*Table 2. Paired-Samples t-Test of Students' Resume Competency Scores Before and After AI Use*

| Comparison | *t* Value | Degrees of Freedom (df) | *p* Value | 95% Confidence Interval (Lower–Upper) | Effect Size (Cohen's d) |
|---|---|---|---|---|---|
| Post-use – Pre-use (Resume Optimization) | 18.62 | 168 | < 0.001 | 2.45–2.88 | 2.15 |

The results indicate that the successful empowerment of resume optimization tasks stems from their highly structured nature, such as the use of the STAR framework for resume writing, which aligns closely with AI's rule-based processing capabilities. Moreover, from the perspective of variance consistency, the reduction in the standard deviation of post-use competency scores (from 1.23 to 1.05) suggests that the resume AI helps narrow the capability gap among students with different baseline skill levels. In particular, it provides a more pronounced "baseline support effect" for students with initially weaker abilities, thereby offering empirical evidence for the broader adoption of resume AI in higher education contexts.

In such tasks, AI demonstrates efficiency and consistency that can surpass human performance, a finding further supported by interview data. As one respondent (Participant No. 3) noted: "Before, I had to wait one or two days for a teacher to revise my resume… Now with AI, it's done in seconds. It also rewrites my internship experience in a very professional way and adds data, making it look much more polished." This highlights the core value of AI in this context: enhanced efficiency combined with quality assurance. Within highly compatible task scenarios, the TPC transmission chain forms a virtuous cycle characterized by "high task–technology fit → frequent and in-depth usage → high-performance outcomes." Here, AI's empowering mechanism manifests as an "efficiency substitution" for repetitive human labor, effectively freeing career counselors from time-consuming text revision tasks. However, a small number of interviewees also noted that AI-generated resumes may exhibit a certain degree of "templated" uniformity, requiring final review and refinement by counselors. This exception further underscores the necessity of human–machine collaboration.

### *3.2 Mechanism II: "Capability Enhancement" in Semi-Structured Tasks*

This mechanism applies to semi-structured tasks—such as simulated interviews—that combine both rule-based elements and situational flexibility. Such tasks are characterized by the coexistence of frequently recurring standardized questions and uncertainty arising from contextual variation. Scholarly perspectives on the role of technology in these tasks remain divided: some studies regard AI as an effective tool for foundational training, while others emphasize the irreplaceable role of human guidance [6]. From a data perspective, the AI interview agent exhibits a pattern of "moderate coverage and high user engagement." Among the 207 respondents, 93 students (44.9%) reported using this function. Although its adoption rate is lower than that of the resume optimization tool, user engagement and retention are notably stronger.

© 2026 by the author(s); licensee Mason Publish Group, this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (http://creativecommons.org/licenses/by/4.0/)

*Table 3. Descriptive Statistics of Students' Interview Competency Scores Before and After Using the AI Interview Agent (Interviewer Lulu)*

| Indicator | Before Use (Pre-Intervention) | After Use (Post-Intervention) | Difference (Post – Pre) |
|---|---|---|---|
| Sample Size (n) | 93 | 93 | 93 |
| Mean (M) | 5.91 | 7.55 | 1.64 |
| Standard Deviation (SD) | 1.38 | 1.12 | 0.95 |
| Minimum | 3.00 | 5.00 | 0.80 |
| Maximum | 8.00 | 9.50 | 3.20 |

Before using the AI interview agent, students' self-assessed interview competency had a mean score of 5.91 (SD = 1.38), indicating a below-moderate overall level of performance. The relatively large standard deviation (1.38) suggests substantial variation in baseline interview skills across students. After using the AI tool, the mean score increased to 7.55 (SD = 1.12), representing a 27.7% improvement. At the same time, the standard deviation decreased to 1.12, indicating that the AI not only enhanced overall interview performance but also reduced disparities among students, reflecting a "standardized empowerment" effect.

Results from the paired-samples t-test (see Table 4) show that students' interview competency scores after using the AI agent were significantly higher than before, $t(92) = 14.36$, $p < 0.001$. Further calculation yields a large effect size (Cohen's $d = 1.82$), indicating a substantial practical impact of the AI interview agent on improving students' interview performance.

*Table 4. Paired-Samples t-Test of Students' Interview Competency Scores Before and After Using the AI Interview Agent (Interviewer Lulu)*

| Comparison | *t* Value | Degrees of Freedom (df) | *p* Value | 95% Confidence Interval (Lower–Upper) | Effect Size (Cohen's d) |
|---|---|---|---|---|---|
| Post-use – Pre-use ( interview agent) | 14.36 | 92 | <0.001 | 1.42-1.86 | 1.82 |

The AI interview agent significantly improves students' interview performance, with an average increase of 1.64 points (on a 10-point scale), representing a 27.7% gain. This provides strong empirical support for the effectiveness of the "AI-driven capability enhancement mechanism" in semi-structured tasks. Through standardized question simulation and real-time feedback, the tool enables students to rapidly acquire foundational interview skills. The standard deviation of competency scores decreased from 1.38 to 1.12 after use, indicating that the AI's standardized training helps lower-performing students address key weaknesses—such as response structure and fluency—while preventing higher-performing students from stagnating. As a result, disparities in interview competence across students are effectively reduced, highlighting the tool's "inclusive" value in career guidance. These findings provide a foundation for developing a collaborative model that combines "AI-based foundational training" with "advanced guidance from career counselors." A key insight from the interviews is the "psychological safety zone" created by AI. As Participant No. 2 noted: "When practicing

© 2026 by the author(s); licensee Mason Publish Group, this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (http://creativecommons.org/licenses/by/4.0/)

with a real instructor, I feel nervous and afraid of making mistakes… but with AI, I can speak freely. Even if I say something wrong, it's not embarrassing, and I can practice repeatedly." This low-pressure simulation environment greatly encourages deliberate practice, aligning closely with the TPC framework's transmission logic of "task–technology fit → usage behavior." Importantly, counselors' post-practice feedback plays a critical moderating role. AI serves as a foundational "practice partner," helping students become familiar with interview procedures and reduce anxiety, while counselors act as "advanced coaches," providing targeted feedback based on students' performance. This is particularly valuable in complex scenarios—such as leaderless group discussions and stress interviews—where AI struggles to replicate the dynamics of real interpersonal interaction. While AI effectively addresses the foundational issues of "daring to interview" and "knowing how to interview," the integration of human guidance is essential for meeting more advanced needs related to personalization and depth, thereby enhancing the overall effectiveness of career guidance.

### *3.3 Mechanism III: "Trust Inhibition" in Low-Structured Tasks*

This mechanism centers on low-structured tasks that require deep self-exploration and emotional resonance. The career planning agent provides services such as career direction selection and developmental pathway planning, while the psychological counseling agent offers support for job-search anxiety and emotional regulation following setbacks. Both types of agents operate in domains where relational trust and empathic understanding are critical. Analysis of the 207 survey responses reveals that these two types of agents exhibit a clear pattern of "low adoption, low trust, and low empowerment." Their usage rates range from 16.9% to 20.3%, significantly lower than those of the resume AI (81.6%) and interview AI (44.9%). Moreover, over 83.3% of users discontinued use after a single interaction, and none adopted the core recommendations provided by the tools. Although there were slight increases in students' self-assessed competencies after use (ranging from 0.53 to 0.66 points), paired-samples t-tests indicate that these differences are not statistically significant ($p > 0.05$). These findings provide empirical support for the existence of a "trust inhibition mechanism" in low-structured tasks. AI systems struggle to establish the "relational trust" required for effective career planning and psychological support, resulting in a breakdown of the TPC transmission chain characterized by "low trust → shallow usage → limited empowerment." At the same time, these results offer important implications for defining the boundaries of human–machine collaboration in university career guidance. While such AI agents may serve as auxiliary tools for providing industry information or offering light emotional support, core functions—such as clarifying career values and delivering deep emotional guidance—must continue to rely on the human-led role of career counselors.

## 4. Differentiated Empowerment: Trust Mode Transformation and the Dynamic Matching Mechanism of Human–Machine Collaboration

The differences observed across the three empowerment mechanisms discussed above fundamentally stem from shifts in trust modes within the Task–Performance Chain (TPC), as well as the reconfiguration of role positioning. These differences also reflect the dynamic nature of human–machine collaboration across varying task contexts.

© 2026 by the author(s); licensee Mason Publish Group, this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (http://creativecommons.org/licenses/by/4.0/)

### *4.1 From "Instrumental Trust" to "Relational Trust": The Trust Threshold in TPC Transmission*

This study finds that students' trust in AI agents exhibits a clear stratification, which directly affects the continuity of the TPC transmission chain. Instrumental trust is grounded in a rational evaluation of the AI's performance and utility. Prior research suggests that in highly and moderately standardized tasks, trust in machines is more pronounced [7], a pattern that aligns with the use of resume optimization and interview simulation agents in this study.

For instance, when revising resumes, students primarily focus on the quality of revisions, while in interview practice, they are concerned with training effectiveness. In such goal-oriented scenarios, as long as the AI demonstrates sufficient capability, trust can be rapidly established, thereby promoting deeper engagement and ensuring the smooth operation of the TPC transmission chain. However, instrumental trust and relational trust are not entirely separate; even in highly standardized tasks, a limited degree of relational trust may still be present, albeit to a lesser extent. This observation receives modest support from a small number of interview responses in this study.

In contrast, relational trust depends more on affective perceptions of goodwill and empathy in the interaction partner and is typically activated in low-structured tasks. For example, when students struggle with career decisions—such as choosing between public sector employment and private enterprise—they do not merely seek an optimal solution derived from data, but rather emotional support that acknowledges their uncertainty and resonates with their personal concerns. However, due to its inherent technological nature, AI is limited in its ability to fulfill such emotional needs, resulting in the failure to establish relational trust and, consequently, the disruption of the TPC transmission chain.

Overall, the degree of task standardization fundamentally determines which mode of trust students rely upon in a given context. Instrumental trust represents the domain in which AI can effectively operate and serves as the key enabler of a functional TPC transmission chain in highly and moderately standardized tasks. In contrast, relational trust constitutes the core value of human counselors, forming a "moat" that AI cannot easily cross, and serving as a critical prerequisite for the successful operation of the TPC transmission chain in low-structured tasks.

### *4.2 Redefining the Role of Counselors*

After clarifying the capability boundaries of AI and the transmission mechanisms within the Task–Performance Chain (TPC), the role of counselors should not be framed as competing with AI. Instead, they should actively embrace this transformation, moving away from the traditional "all-purpose caretaker" role and repositioning themselves as managers of the intelligent system as a whole, assuming multiple, higher-value roles within human–AI collaboration.

This division of roles is not static; rather, it dynamically adjusts according to the degree of alignment between task characteristics and technological capabilities. Based on the present findings, in highly compatible tasks such as résumé revision, AI can undertake approximately 80% of standardized content optimization. In such contexts, counselors primarily function as quality controllers and strategic optimizers: after AI generates

© 2026 by the author(s); licensee Mason Publish Group, this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (http://creativecommons.org/licenses/by/4.0/)

an initial draft, counselors can redirect their time toward more critical tasks, such as assessing whether the content is overly embellished and aligning the résumé with long-term career development trajectories. When AI-generated drafts deviate from appropriate directions, the counselor's gatekeeping role becomes even more essential.

In moderately compatible tasks such as mock interviews, empirical observations suggest that AI is best suited as a foundational "practice partner," while counselors should elevate their role to that of advanced coaches and scenario designers. They can help alleviate students' anxiety by organizing complex simulations—such as leaderless group discussions and stress interviews—that AI currently struggles to authentically replicate. Additionally, counselors provide targeted guidance on nuanced aspects such as body language and facial expression management, which remain beyond the effective reach of current AI systems.

For low-compatibility tasks such as psychological counseling and career planning, this study finds that AI can only function as a supporting tool, whereas counselors serve as the primary companions and guides of values. While AI may offer generic comforting language or data-driven suggestions, deeper functions—such as emotional resonance, value clarification, and crisis intervention—depend fundamentally on the trust-based relationships established between counselors and students. This form of empathetic human connection constitutes a core competency that technology is unlikely to replicate.

### *4.3 Empirical Validation of the TPC Chain Transmission Mechanism*

This study further empirically validates the applicability of the Task–Performance Chain (TPC) theory within the context of AI-powered employment guidance agents. Prior research suggests that task–technology fit does not directly determine empowerment outcomes; rather, it operates through students' usage behavior as a key mediating variable, forming a transmission pathway of "task characteristics + technology characteristics → fit → usage behavior → empowerment outcomes."

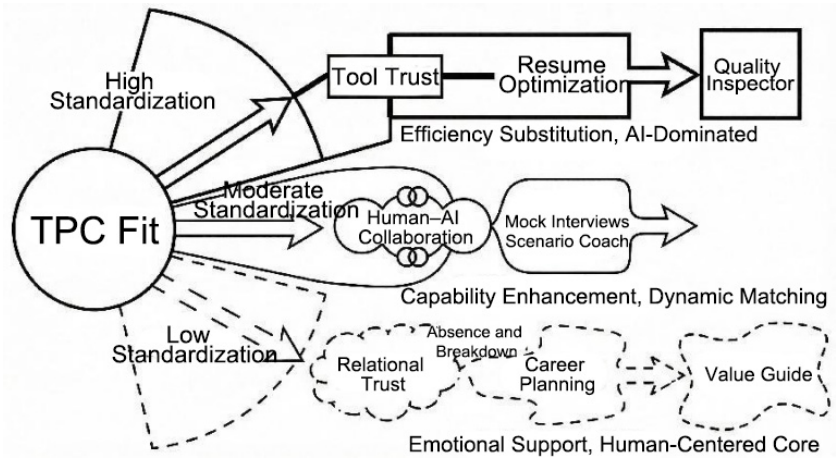



*Figure 1. Applicability of TPC Theory in AI-Powered Employment Guidance Scenarios*

Specifically, in highly standardized tasks, a high level of fit directly promotes frequent and in-depth use of AI tools by students. This sustained usage, in turn, reinforces the efficiency substitution effect, forming a positive feedback loop of "fit → increased use → higher efficiency," through which the TPC transmission chain operates smoothly and fully. In semi-structured tasks, a moderate level of fit encourages continued use by

© 2026 by the author(s); licensee Mason Publish Group, this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (http://creativecommons.org/licenses/by/4.0/)

creating a "psychological safety zone" for students. Meanwhile, counselors' reflective guidance functions as a moderating variable, further amplifying the conversion from tool usage to capability enhancement. In contrast, in low-structured tasks, insufficient fit—primarily due to the absence of relational trust—discourages students from engaging in deep use of AI agents. As a result, the transmission chain of "fit → usage → outcomes" is effectively disrupted, limiting the potential for meaningful empowerment. These findings not only enrich the empirical foundation of TPC theory in the domain of educational AI agents but also provide a new analytical lens for understanding the differentiated effects of technological empowerment.

# 5. Conclusions and Implications: Constructing a "Tiered and Streamlined" Human–AI Collaboration Pathway

## *5.1 Theoretical Contributions and Empirical Findings*

This study empirically validates and extends the applicability of the Task–Performance Chain (TPC) theory in the domain of educational AI agents. Its primary theoretical contributions are threefold. First, it identifies the degree of task standardization as a critical antecedent variable that fundamentally shapes the initial stage of the TPC transmission chain—namely, task–technology fit. Second, it confirms the role of usage behavior as a core mediating variable that bridges the relationship between fit and empowerment outcomes. Third, it reveals the moderating effects of trust modes and counselor support on the smooth functioning of the TPC transmission chain. The empirical findings indicate that while the alignment between task standardization and technological capability serves as a foundational determinant of AI-enabled employment guidance effectiveness, it is not the sole factor. AI empowerment exhibits a tiered pattern characterized by efficiency substitution, capability enhancement, and trust obstruction, which essentially reflects varying degrees of fluidity within the TPC transmission chain. Moreover, students' trust in AI demonstrates strong context dependency; technology alone cannot fully bridge the emotional gap between humans and machines. The transformation of counselors' roles, therefore, emerges as a key condition for ensuring the effective operation of the TPC chain across diverse scenarios.

## *5.2 Limitations and Future Directions*

This study is subject to several limitations. The sample is relatively narrow, being drawn from a single college and a specific academic discipline, which may constrain the generalizability of the findings. In addition, the measurement of usage behavior relies primarily on self-reported data, lacking more objective behavioral indicators. Future research could address these limitations by expanding the sample to include diverse types of higher education institutions and academic disciplines, thereby further testing the robustness of the TPC framework. Incorporating more objective validity measures would also enhance the assessment of empowerment outcomes. Furthermore, as AI technologies continue to evolve, the boundaries and modalities of human–AI collaboration are likely to shift. Longitudinal studies tracking the impact of technological advancements on the TPC transmission mechanism would provide more timely theoretical insights and practical guidance for the digital transformation of university career services.

© 2026 by the author(s); licensee Mason Publish Group, this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (http://creativecommons.org/licenses/by/4.0/)

## Funding

This research was supported by the 2025 Student Affairs Research Project of Guangdong University of Finance, titled “Pathways and Practical Applications of Agent-Based Empowerment for Enhancing the Efficiency of Employment Services” (Project No. GJXG202509).

## References

[1]Brown, T., Mann, B., Ryder, N., et al. (2020). Language models are few-shot learners. Advances in Neural Information Processing Systems, 33, 1877–1901.

[2]Zhang, Y., Zhu, J., Dong, W., Li, F., & Guo, L. (2024). Construction process and technological prospects of large language models in the agricultural vertical domain. Journal of Agricultural Big Data, 6(3), 412–423.

[3]Ren, Y., Tan, K., Li, B., & Yuan, L. (n.d.). Artificial intelligence–empowered enhancement of public digital cultural services: Construction of vertical-domain AI agents. Information and Documentation Services, 1–25. (Advance online publication)

[4]Mu, Z., Yue, T., & Zhu, T. (2025). Personalized learning design based on cognitive intelligent large models from the perspective of human–machine collaboration. E-Education Research, 46(2), 80–87.

[5]Li, L., Yang, H., Tan, Y., & Jian, Z. (2016). A review and future prospects of task–technology fit theory. Foreign Economics & Management, 38(1), 29–41.

[6]Ding, F. (2025). Can AI replace human thinking in the “post-human era”? Contemporary Writers Review, (3), 44–52.

[7]de Visser, E. J., Pak, R., & Shaw, T. H. (2018). From “automation” to “autonomy”: The importance of trust repair in human–machine interaction. Ergonomics, 61(10), 1409–1427. https://doi.org/10.1080/00140139.2018.1457725

© 2026 by the author(s); licensee Mason Publish Group, this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (http://creativecommons.org/licenses/by/4.0/)