Closing the 'Cognitive Last Mile': How Agentic AI Empowers Teachers' Self-Efficacy in Career Counseling

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Abstract

The expansion of high school credit systems has increased teachers' responsibilities in career counseling, requiring them to integrate fragmented student data with rapidly evolving external career information. Although generative AI systems are increasingly adopted to assist counseling tasks, responsibility for integrative reasoning and verification remains with teachers, creating a structural gap we term the *cognitive last mile*. This study investigates whether an agentic AI-based career counseling system can address this gap by redistributing reasoning and verification demands from teachers to internal inter-agent processes. Twenty high school teachers interacted with a multi-agent system designed to support counseling preparation and practice. Using a retrospective pre–posttest design and semi-structured interviews, we examined changes in teachers' career-related support self-efficacy (TCSSE). Results showed significant improvements across all six TCSSE dimensions, suggesting that architectural designs that internalize reasoning and verification within multi-agent systems may help address the cognitive last mile while preserving teachers' professional judgment.

Keywords

Agentic AI, Career Counseling, Teacher Self-Efficacy, Teacher–AI Co-Agency, Cognitive Last Mile

1. Introduction

The expansion of high school credit systems has fundamentally reshaped teachers' responsibilities in career counseling, shifting their role from information providers to integrative decision-makers [1]. Teachers are now expected to interpret rapidly evolving external career information—such as labor market trends and educational pathways—through the lens of rich student data, including academic records and interests [2, 3]. This integrative work must be performed under severe time constraints and across fragmented information sources, imposing cognitive demands that constrain teachers' capacity to provide effective, individualized career counseling [4].

In response, generative AI systems have been introduced to support counseling tasks, demonstrating efficiency in information retrieval, summarization, and content generation [5, 6, 7]. However, current generative AI systems lack the ability to autonomously structure information, reason across multiple data sources, or verify context-sensitive outputs [8]. Responsibility for integrative processes—reasoning across student data and verifying external career information—therefore remains with teachers [9, 10]. This creates a structural paradox: while generative AI may reduce surface-level workload, it shifts cognitive accountability for reasoning and verification onto teachers.

We conceptualize this persistent challenge as the *cognitive last mile*: a structural condition in which essential integrative processes (e.g., cross-source reasoning and verification) remain unresolved by current generative AI systems and must be completed by teachers. When left unaddressed, AI support risks increasing teachers' cognitive burden and may erode their career-related support self-efficacy (TCSSE) [11].

To address this limitation, we propose an agentic AI approach that redistributes reasoning and verification across role-specialized agents within a multi-agent architecture. This study investigates:

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(1) how an agentic AI-based career counseling system affects teachers' TCSSE, and (2) how teachers experience changes in their self-efficacy while engaging with agentic AI during counseling.

2. Related Work

Career-related support self-efficacy refers to teachers' perceived capability to provide effective career guidance [11]. From a self-efficacy perspective [12, 13], such beliefs are sustained primarily through mastery experiences—repeated enactments of successful professional performance. However, current generative AI systems do not support this process. While they reduce surface-level workload through information retrieval and summarization [5, 7, 14], they externalize the integrative cognitive processes central to career counseling—reasoning across student data and verifying external career information—to teachers [9, 10, 8]. This positions teachers as validators of AI outputs rather than agents of successful counseling outcomes, limiting the mastery experiences that underpin TCSSE. Despite growing AI adoption in counseling contexts, empirical evidence on how AI system design affects TCSSE remains limited [6].

Agentic AI addresses this gap at the system level. Unlike conventional generative AI, which produces outputs through a single inference pass, agentic AI coordinates multiple role-specialized agents that plan, act, and verify iteratively [15, 16]. By internalizing reasoning and verification within a multi-agent architecture, such systems manage inter-agent coordination internally—reframing AI support from content generation to the structural management of professional cognitive work, and thereby creating conditions under which teacher agency can be preserved or strengthened [6].

3. Methods

3.1. Participants and Procedure

Twenty high school teachers participated in the study. All were either homeroom teachers or career guidance teachers actively responsible for career counseling in their schools. The study employed a mixed-methods design with a retrospective pre–posttest approach, appropriate when participants' understanding of the target construct is expected to evolve during an intervention [17]. Participants attended an initial orientation session and used the agentic AI-based career counseling support system for three weeks during both counseling preparation and practice. Each teacher conducted individual career counseling sessions with at least five students as part of their routine activities. After the intervention, participants completed the TCSSE retrospective pretest and posttest, followed by semi-structured interviews. Because student records were used as system inputs during counseling, informed consent was obtained from all participating teachers as well as from the students and their parents. All data were anonymized prior to analysis, and the study protocol was approved by the institutional review board.

3.2. System Design

Building on the two core cognitive functions identified above—reasoning and verification—the system was designed to internalize these within its architecture. Here, reasoning refers to interpreting contextual relationships across fragmented student data, while verification refers to grounding externally sourced career information for relevance and currency. The system adopts a multi-agent architecture comprising three role-specialized agents: (1) Context Agent: integrates student data to construct individualized counseling perspectives; (2) Exploration Agent: retrieves and updates external career information through web and API queries to maintain temporal relevance; and (3) Validation Agent: synthesizes agent outputs through iterative cross-checking and self-correction to ensure analytical coherence. Specifically, the Validation Agent performs self-correction by reviewing Exploration Agent outputs for internal coherence and alignment with the Context Agent's student profile, regenerating responses when inconsistencies are detected. Rather than relying on single-pass prompting techniques such

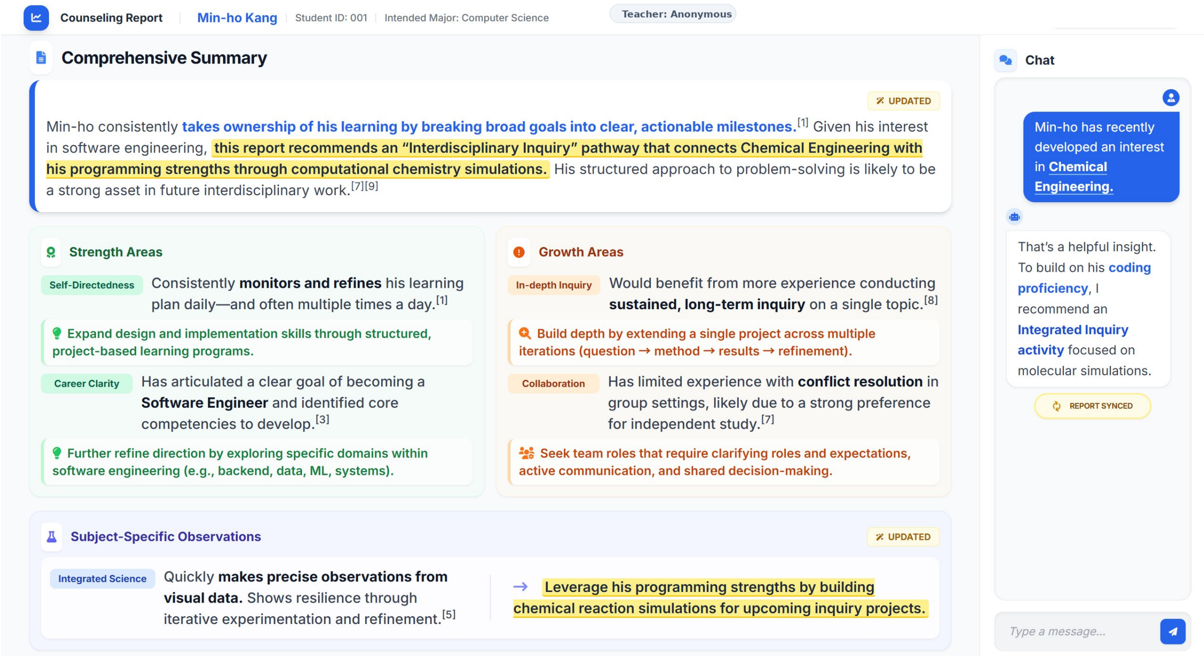

Figure 1: Two primary interfaces of the agentic AI-based career counseling support system. The system-generated counseling report (left) presents insights produced through inter-agent reasoning and verification. The interactive chat interface (right) enables teachers to iteratively engage with the system by requesting additional reasoning and updating student information.

as chain-of-thought, the system distributes reasoning across role-specialized agents, with each agent guided by structured prompts that decompose the counseling task into explicit subgoals, enabling traceable inter-agent reasoning.

Participants interacted with the system through two primary interfaces: system-generated counseling reports and an interactive chat interface (see Figure 1). During counseling preparation, teachers reviewed reports and used the chat interface to refine counseling focus or request additional reasoning. During counseling practice, teachers referenced reports while engaging with students and entered newly obtained information into the chat interface, triggering renewed inter-agent interactions and updated analyses. This structure allowed teachers to remain primary facilitators of counseling interactions while shifting reasoning and verification demands to internal inter-agent processes. The system was implemented in Streamlit and integrated with the GPT-4o API.

3.3. Measures and Analysis

Teachers' TCSSE was assessed using the validated TCSSE questionnaire [11], which consists of 36 items across six dimensions rated on a five-point Likert scale: *Get Ready* (motivating students to prepare for their professional future); *Empower Self* (fostering students' autonomous decision-making and personal responsibility); *Get Curious* (promoting career exploration and investigation of the world of work); *Empower Skills* (developing students' life skills and competencies, such as resilience and creative problem-solving); *Emotional Support* (helping students recognize their personal strengths and build self-confidence); and *Instrumental Support* (providing practical career information, vocational guidance, and professional pathway support). Paired-samples t-tests were conducted for each dimension to examine changes in perceived self-efficacy. Semi-structured interviews provided qualitative evidence for how changes were experienced in practice.

Table 1
Changes in TCSSE across retrospective pretest and posttest ($n = 20$)

Dimension	Pretest	Posttest	p
Get Ready	4.09 ± 0.54	4.43 ± 0.53	$< .001^{***}$
Empower Self	4.02 ± 0.61	4.25 ± 0.48	$< .01^{**}$
Get Curious	3.85 ± 0.53	4.40 ± 0.41	$< .001^{***}$
Empower Skills	3.93 ± 0.56	4.12 ± 0.50	$< .05^{*}$
Emotional Support	3.98 ± 0.49	4.56 ± 0.36	$< .001^{***}$
Instrumental Support	3.90 ± 0.48	4.42 ± 0.39	$< .001^{***}$

Note. Values are mean ± SD on a 5-point Likert scale. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

4. Results

4.1. Changes in Teacher Career-Related Support Self-Efficacy

Paired-samples t-tests revealed significant improvements between the retrospective pretest and posttest across all six TCSSE dimensions (Table 1). On the 5-point Likert scale, mean scores rose from a moderate-to-high baseline (range: $M = 3.85$–4.09) to consistently higher levels at posttest (range: $M = 4.12$–4.56). The overall TCSSE composite, computed by averaging across all 36 items, also increased significantly, from $M = 3.96$ ($SD = 0.50$) at retrospective pretest to $M = 4.34$ ($SD = 0.39$) at posttest, $t(19) = 5.32$, $p < .001$.

To characterize the magnitude of these within-subject changes, we computed Cohen's d_z for each dimension. Effect sizes ranged from $d_z = 0.57$ (Empower Skills) to $d_z = 1.28$ (Emotional Support), with five of the six dimensions showing large effects ($d_z > 0.80$) and the overall composite yielding $d_z = 1.19$. These results indicate that teachers' perceived self-efficacy in providing career-related support improved reliably and substantively across the breadth of competencies measured by the TCSSE following the three-week intervention.

4.2. Qualitative Findings

Thematic analysis of the interviews provided converging evidence across all six TCSSE dimensions. During counseling preparation, system-generated reports reduced uncertainty and supported confident session initiation, while AI-supported reasoning strengthened teachers' self-efficacy in facilitating student-centered dialogue. During counseling practice, real-time updates sustained exploratory questioning, competency-aligned guidance, empathetic engagement, and timely provision of practical career information. For example, one teacher explained, "As an English teacher, I had difficulty counseling students in the science track. The AI provided up-to-date information on academic departments and occupational data, which helped me bridge the information gap and complement my counseling expertise." Across dimensions, participants described meaningful shifts in their counseling practice, suggesting the agentic AI system supported teachers not merely through information access but by internalizing the reasoning and verification demands of the cognitive last mile.

5. Discussion and Conclusion

This study suggests that an agentic AI-based career counseling system can enhance TCSSE across all six dimensions, functioning not merely as an efficiency tool but as an intervention that reshapes how teachers experience professional cognitive work. These gains may be attributable to a design that aims to internalize reasoning and verification within the AI system itself. Whereas conventional generative AI leaves teachers responsible for the cognitive last mile, the agentic system shifts these demands to coordinated inter-agent processes—enabling teachers to focus on professional judgment rather than output validation, and thereby generating the positive counseling experiences that appear to sustain their self-efficacy.

These findings carry direct implications for the HAI-Agency research agenda. They suggest that agentic AI orchestration need not diminish teacher agency: when AI systems internalize cognitive labor rather than externalize it, they may actively strengthen teachers' sense of professional competence. The cognitive last mile concept offers a concrete diagnostic framework for identifying where AI designs undermine human agency—not in output quality, but in the structural allocation of cognitive work. Concretely, the multi-agent architecture examined here operationalizes teacher–AI co-agency in practice: teachers retained contextual interpretation and final authority, while AI agents managed reasoning and verification internally. This study thus shifts the focus from output quality to cognitive labor structure, suggesting that sustainable teacher–AI co-agency depends on designs that preserve, rather than erode, the conditions for professional mastery.

These findings should be interpreted within the scope of an exploratory study. The sample size ($n = 20$) reflects the in-depth, multi-week nature of the intervention and constrains broad generalization. To address potential response shift bias in self-reported change, we adopted the retrospective pre–posttest design, which controls for participants' evolving understanding of the target construct during the intervention [17]. The present study also prioritized teachers' experiential outcomes as the primary research goal; systematic benchmarking of agent outputs against objective metrics (e.g., factuality, faithfulness) is a planned follow-up. Building on these preliminary findings, future research employing larger-scale randomized controlled trials across diverse school contexts would extend the present results toward stronger causal claims.

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Declaration on Generative AI

The authors have not employed any Generative AI tools.

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