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Optimization of Research Framework Driven by Human-AI Collaboration: An Empirical Study on AI Training and Vulnerable Employment Groups

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Abstract: Taking the improvement of skills and literacy among vulnerable employment groups through AI practical training as a case, this study illustrates how to achieve iterative optimization of a research hypothesis framework based on first-hand interview data via the collaborative use of DeepSeek and ChatGPT. Grounded in the Technology Acceptance Model (TAM), the study establishes an initial framework, collects interview data from vulnerable employment group volunteers who completed AI practical training, and uses AI-based transcription to form analytical texts. By inputting the initial framework and interview transcripts into the two AI models for exploratory optimization analysis, comparing and integrating their suggestions, and combining the researcher's in-depth interpretation of raw data, the research framework is ultimately reconstructed. The findings clarify the deficiencies of the initial framework and provide a human-AI collaborative research paradigm of dual-model cooperation plus researcher judgment, offering a replicable methodological example for the iterative optimization of research frameworks. This work contributes to advancing SDG 4 (Quality Education) by enhancing access to skill development, supports SDG 8 (Decent Work and Economic Growth) through empowering vulnerable workers, and promotes SDG 9 (Industry, Innovation and Infrastructure) by demonstrating innovative applications of AI in social research.

Keywords: Research framework optimization; TAM model; Human-AI collaboration; Vulnerable employment groups; Empirical study; SDGs

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1. Introduction

The Research Framework constitutes the cornerstone of empirical research. In conventional research, researchers typically develop a hypothesized model based on a literature review and then validate it using data[1]. However, when the research population is distinctive—such as vulnerable employment groups—and the technological context evolves rapidly, existing theories may require contextual adaptation[2, 3]. Vulnerable groups face multiple structural barriers, including inadequate digital infrastructure, limited exposure to emerging technologies, and scarce practical opportunities, which profoundly shape their technology acceptance and capability development, necessitating context-specific adjustments to classic models[4].

In recent years, large language models have demonstrated strong capabilities in pattern recognition and semantic understanding for textual analysis. The quality of human-AI collaboration is structured along three dimensions: outcome quality, comfort, and efficiency, with user agency as the core driver of high-quality collaboration[5]. Against this background, this study explores the integration of DeepSeek and ChatGPT into Research Framework optimization, establishing a new paradigm of human-AI collaboration[6]. Using the project "enhancing skills and literacy of vulnerable employment groups through AI practical training" as an empirical setting, it demonstrates how dual-model collaborative analysis can identify inconsistencies between theory and data and support the iterative refinement of the hypothetical framework based on in-depth interview texts.

2. Research method

2.1. Initial research framework

Drawing on the Technology Acceptance Model (TAM)[7, 8] and the characteristics of vulnerable employment groups, this study initially constructed a framework consisting of 12 hypotheses (H1–H12), covering perceived usefulness, perceived ease of use, individual innovativeness, intention to use, actual usage behavior, AI literacy, and new-quality employability. AI practical training, technology-task fit, and organizational support were introduced as moderating variables. Based on TAM2, Amouri et al. (2025)[9] showed that perceived usefulness is the strongest predictor, while subjective norms and voluntariness also play significant roles, highlighting the importance of social support factors, which provided a reference for the initial framework design. An initial research framework was developed to inform the analytical process, as shown in **Figure 1**.

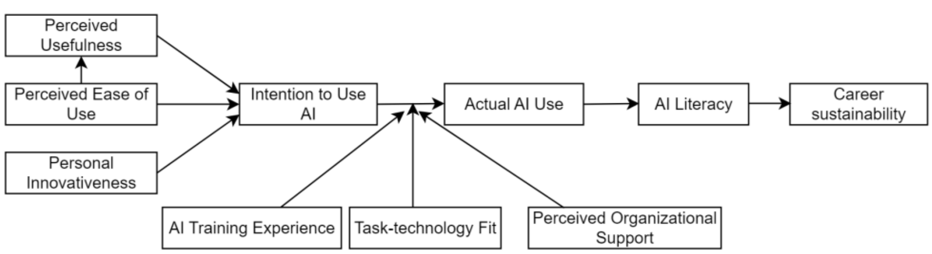

Figure 1. presents the initial research framework guiding this study.

2.2. Interview design and data collection

A semi-structured interview guide was developed based on the initial framework, covering perceptions of AI usefulness and ease of use, changes before and after training, AI usage behavior and frequency, manifestations of AI literacy, employment-related impacts, and external support. Six valid interviews were collected from volunteer trainees who had completed AI practical training, recruited via training partners; their backgrounds include a liberal arts postgraduate (01), a sales practitioner (02), an unemployed job seeker (03), a general clerk (04), a fresh design graduate (05), and a vocational college student (06), representing diverse types of vulnerable employment groups.

Each interview lasted 10–25 minutes, flexibly adjusted according to participants' responses, with timely redirection when off-topic. Interview recordings were transcribed using AI tools; interviewers' questions were removed, and only interviewees' original responses were retained, resulting in approximately 18,000 words of analytical text. This treatment adheres to the interviewee-centered analytic principle for interview research, ensuring the authenticity and validity of the research data[10].

2.3. Dual-model collaborative analysis procedure

The analysis proceeded in four sequential stages to ensure the rigor and systematicness of the framework optimization. Stage 1 is data preparation: the initial research framework (complete list of H1–H12) and six de-identified interview texts containing only interviewee responses were organized into two separate input files to facilitate AI model analysis. Stage 2 involves independent dual-model analysis: the original framework, research theme, and six cleaned interview texts were simultaneously submitted to DeepSeek and ChatGPT for exploratory optimization analysis, allowing each model to independently identify potential deficiencies and optimization directions of the framework[6].

Stage 3 focuses on the comparison and integration of suggestions: outputs from both models were juxtaposed to identify convergent recommendations and divergent points, and the researcher verified and synthesized the models' judgments against the raw texts to avoid bias from a single model. Stage 4 is framework iteration: based on integrated optimization suggestions and a literature review, the research framework was reconstructed to achieve theoretical improvement. This process aligns with the human-AI collaborative system evaluation framework proposed by[11], which emphasizes that, on the basis of AI-assisted analysis, researchers retain primacy in theoretical depth, contextual understanding, and value judgment. The analytical procedure is illustrated in Figure 2.

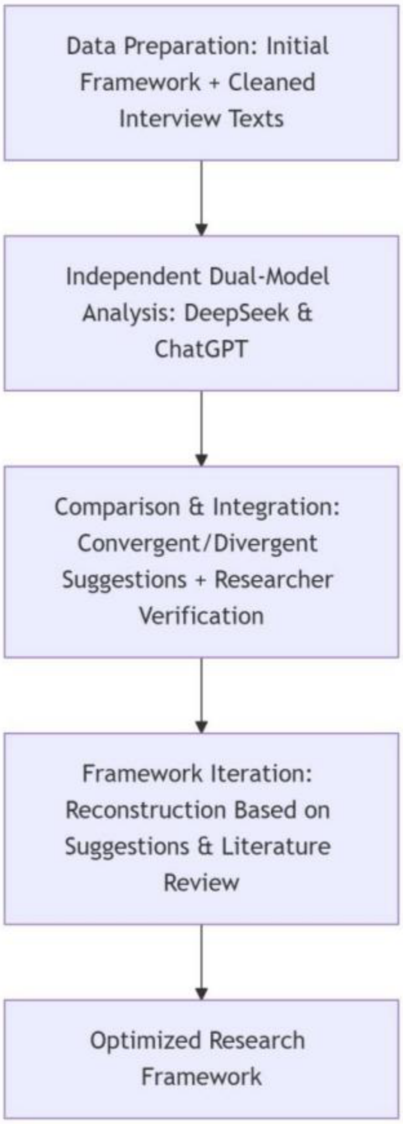

Figure 2. Dual-model collaborative analysis procedure for framework optimization.

3. Research findings

3.1. Finding 1: addition of the path perceived ease of use → perceived usefulness (H2a)

Empirical evidence indicates that five out of six interviewees explicitly expressed the narrative pattern: "it is not difficult after getting started, and it is truly useful." Relevant interview quotes include:

(1) 03_ysy_B: "After getting started, I found the principle is not that complicated. It's really easy to use and learn."

(2) 06_sjh_B: "After the training, I really feel that AI is a very useful skill and very easy to master if I have access to it."

AI recognition and suggestions show that DeepSeek detected the high-frequency co-occurrence of "simple" / "easy" with "useful" / "helpful" in five interviews and recommended testing the effect of perceived ease of use on perceived usefulness. ChatGPT similarly identified this pattern and noted that ease-of-use experience generally served as a prerequisite for perceived usefulness. Consistent with classic TAM, both models and data jointly support the addition of the hypothesis H2a: Perceived ease of use positively influences perceived usefulness, making up for the deficiency of the initial framework in the path between these two core variables[7, 12].

3.2. Finding 2: reconstructing ai practical training from moderating variable to competency antecedent

Comparing pre- and post-training narratives of the interviewees, expressions of "difficult / unconfident before training" appeared 10 times, while "not difficult / mastered / confident after training" appeared 12 times across six interviews. Specific interview quotes include:

(1) 04_ljh_B: "It was quite difficult at first… but after the training, I found it's actually quite simple."

(2) 01_lr_B: "I thought it was a bit difficult before the training… After the step-by-step training, I found I could do it too."

(3) 05_wcc_B: "When I could generate illustrations matching my ideas with simple Chinese descriptions for the first time, I suddenly realized I could do it too."

This clear shift in their perceptions of AI use difficulty and self-confidence reflects the significant impact of AI practical training. DeepSeek highlighted that training not only changed perceptions of difficulty but also directly affected judgments of usefulness and self-confidence, recommending that training be repositioned as an antecedent of multiple variables. ChatGPT systematically proposed reconstructing AI training from a moderating variable to a competency catalyst—an antecedent of competency formation that affects perceived usefulness, perceived ease of use, AI literacy, and self-efficacy, transforming the model into a competency formation model with stronger explanatory power.

The integrated suggestions from the two models were adopted in the framework optimization: Hypotheses H7–H9 were revised from moderating effects to direct paths, and H10 was added to clarify the specific mechanism of AI practical training. The revised and added hypotheses are as follows: H7: AI practical training positively influences perceived usefulness; H8: AI practical training positively influences perceived ease of use; H9: Individual innovativeness positively moderates the effect of training on perceived ease of use; H10: AI practical training promotes the conversion of usage intention into actual behavior by lowering perceived barriers.

3.3. Finding 3: three-dimensional operational structure of new-quality employability

Keyword analysis of the interview texts reveals strong clustering around three core dimensions related to new-quality employability. DeepSeek's word co-occurrence network analysis and ChatGPT's thematic classification converged on a three-dimensional structure consistent with Bandura's social cognitive theory, including the competency layer, cognitive layer, and mindset layer[13]. The competency layer is mainly reflected in efficiency, skills, and mastery; the cognitive layer involves thinking, logic, and understanding; and the mindset layer includes confidence, anxiety, and willingness.

Based on this, this study operationalizes new-quality employability into three measurable dimensions to enhance the practicality of the research framework: Competency, which includes human-AI collaboration efficiency and AI tool application ability; Cognition, which covers prompt engineering thinking, information integration, and critical evaluation; and Mindset, which involves employment confidence, willingness to explore new positions, and self-efficacy. The three-dimensional framework of new-quality employability is visually summarized in **Figure 3**.

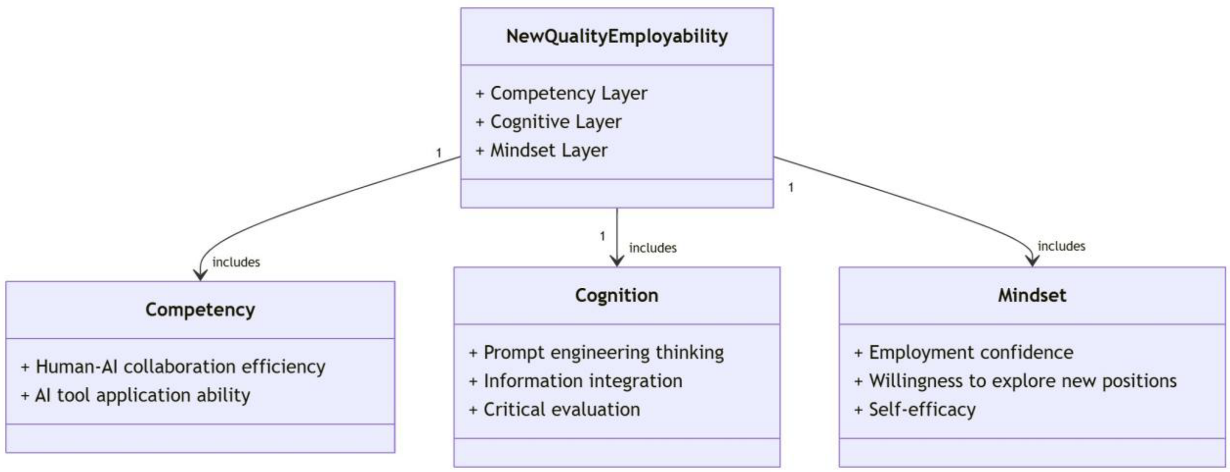

Figure 3. Three-dimensional operational structure of new-quality employability, integrating cognitive, behavioral, and environmental components.

3.4. Treatment of other hypotheses

In addition to the key optimizations mentioned above, other hypotheses in the initial framework were also verified based on interview data and AI analysis results. H11 (technology-task fit) received weak support in the interviews and was retained as an exploratory hypothesis for future in-depth research. H12 (organizational support) was strongly supported across all six interviews, which is consistent with TAM2 findings on subjective norms, confirming the important role of external support in the technology acceptance and capability development of vulnerable employment groups[9].

4. Discussion

4.1. Complementary strengths of the dual-model approach

The dual-model collaboration of DeepSeek and ChatGPT in this study demonstrates obvious complementary advantages, which effectively improve the accuracy and depth of framework optimization. DeepSeek excels in precise quantitative pattern detection, such as identifying word co-occurrence rules and comparing pre- and post-training narrative differences, providing objective data support for framework adjustment[14]. ChatGPT, on the other hand, specializes in semantic interpretation, narrative coherence analysis, and high-level theoretical reconstruction, such as proposing the concept of AI training as a “competency catalyst,” which enriches the theoretical connotation of the framework. Convergent judgments between the two models enhance the credibility of the optimization suggestions, while divergent outputs enable researchers to conduct triangulation verification against raw data, avoiding onesidedness in analysis[6].

4.2. Boundaries of human-ai collaboration and the researcher's role

While AI models provide effective assistance in framework optimization, human-AI collaboration has clear boundaries, and researchers still play a dominant role in the research process[6, 15]. Specifically, researchers maintain authority in three key aspects: first, theoretical justification and alignment with existing literature, ensuring that the optimized framework is consistent with the theoretical context and avoids being disconnected from existing research; second, the contextual and emotional interpretation of vulnerable groups' experiences, which AI models are difficult to fully grasp due to the lack of contextual understanding; third, final value judgments regarding the parsimony, explanatory power, and feasibility of the framework, ensuring that the optimized model is both theoretically rigorous and practically applicable.

4.3. A replicable iterative framework-building procedure

Based on the research practice of this study, a replicable iterative framework-building procedure suitable for exploratory studies is summarized. The workflow includes five key links: data preparation, independent dual-model analysis, comparison and integration of suggestions, researcher verification and adjustment, and framework iteration, which can be cycled until the framework reaches stability. This procedure breaks through the limitations of traditional framework optimization relying solely on researcher experience, integrates the advantages of AI in text analysis, and provides a practical methodological reference for similar exploratory research involving distinctive research populations or rapidly evolving technological contexts. **Figure 4** presents a replicable iterative procedure for framework development.

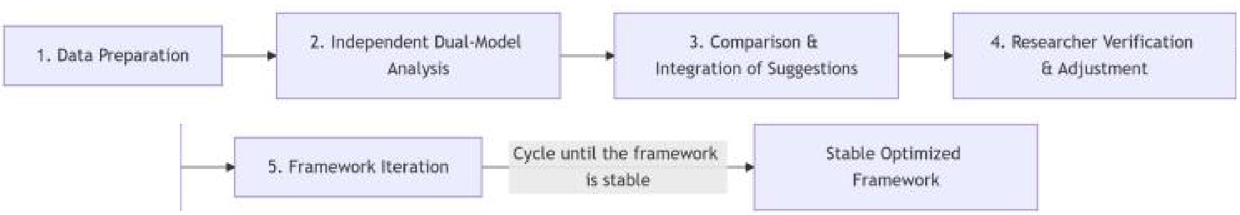

Figure 4. A replicable iterative framework-building procedure.

5. Conclusion

Based on six first-hand interviews, this study demonstrates the feasibility and effectiveness of using DeepSeek and ChatGPT collaboratively to optimize a Research Framework, showing that data-driven framework iteration is feasible even with a small interview sample, and consistent dual-model identification improves the reliability of research findings. The optimized framework makes three key improvements: adding the path from perceived ease of use to perceived usefulness (H2a), redefining AI practical training from a moderating variable to a competent antecedent and elaborating a three-dimensional operational structure of new-quality employability. Future research may extend to larger samples or develop discipline-specific AI prompt templates to further enhance the depth and efficiency of human-AI collaboration, and improving such collaboration also represents an important pathway to reduce digital inequality and advance technological inclusiveness[5], with the dual-model method proposed herein providing an initial exploration in this direction.

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Disclosure statement

The author declares no conflict of interest.

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