Knowledge Internalization Mechanisms in the Feynman Technique

Yan Zhao*

School of Mathematics and Computer Science, Northwest Minzu University, Lanzhou 730030, China

*576610836@qq.com

Abstract. The Feynman technique is often summarized as learning by explaining, but this formula leaves the internal process unclear. This study analyzes a CNKI export of 238 records and retains 156 journal articles from 2017 to June 2026 in which the technique appears in the title or keywords. Descriptive counts and title-abstract-keyword coding identify six recurring dimensions: practice and transfer, knowledge reconstruction, explanation, feedback and diagnosis, collaboration, and digital or AI support. The evidence base is uneven: 93 articles propose a model, 86 report practice-based evaluation, and 42 mention quantitative or comparative evidence. The synthesis defines internalization as a six-stage cycle of selection, reconstruction, explanation, diagnosis, revision, and transfer. For computer experimental education, explanations should be linked to executable procedures, observable data, and repeatable verification.

Keywords: Feynman technique; Knowledge internalization; Learning by teaching; Feedback; Computer experimental education

1 Introduction

The Feynman technique has become visible across Chinese school subjects, vocational education, university courses, clinical training, and computer education. Its appeal is simple: study a topic, explain it plainly, identify what cannot be explained, and return to the material. Yet "teach others" can become a slogan rather than a learning mechanism.

The central issue is knowledge internalization. It is more than retention or fluent speech. In practical courses, students must reorganize knowledge, connect explanations to operations, respond to questions, and apply revised understanding elsewhere. Computer courses use microlectures, projects, and peer discussion [1-4]; medical and experimental studies emphasize simulation, feedback, correction, and repeated performance [5-8].

The literature varies widely in terminology and evidence. Some papers present detailed cycles, others combine the technique with OBE, MOOC, AI, or project learning, and many offer short teaching reflections. Positive outcomes are common, but

Z. Ge et al. (eds.), *Proceedings of the 2026 6th International Conference on Education, Information Management and Service Science (EIMSS 2026)*, Atlantis Highlights in Computer Sciences 25,
https://doi.org/10.2991/978-94-6239-766-8_37

comparison groups are not, and one experiment found no significant score difference despite favorable discussion behavior [7].

This paper asks: through what sequence of actions can the Feynman technique support internalization? It maps the CNKI records, identifies recurring dimensions, and develops a mechanism for computer experiments without treating explanation as an end in itself.

2 Data and Method

The CNKI export contained 238 records from 2017 to 2026: 181 journal articles, 44 theses, eight conference papers, three books, and two newspaper articles. Only journal articles were retained. Twenty-five incidental records were excluded because neither title nor keywords identified the technique, leaving 156 articles. One online-first article was assigned to 2026; data for that year end on June 16.

The bibliometric layer counted annual output and source journals. The content layer coded titles, keywords, and abstracts for six overlapping dimensions: explanation, feedback, reconstruction, collaboration, transfer, and digital or AI support. Three evidence markers were also recorded: model proposal, practice-based evaluation, and quantitative or comparative evidence.

Categories overlapped because one design may combine explanation, platform support, feedback, and transfer. International studies cited for conceptual comparison were outside the 156-record corpus. Counts indicate visibility, not effect size, and claimed improvement was not treated as controlled evidence.

3 Results

3.1 Growth and Distribution

Figure 1 shows that research was sparse from 2017 to 2019, rose sharply in 2020-2021, and expanded again after 2023. The annual count reached 32 in 2024 and 39 in 2025. The 12 articles indexed by June 2026 represent only a partial year. The pattern suggests that the Feynman technique has moved from a study-skills label into a recognizable instructional design term.

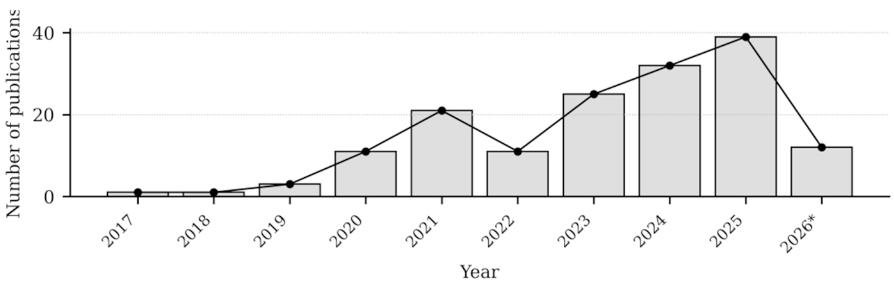

Fig. 1. Annual output of the 156 included journal articles. The 2026 value is partial.

The sources were dispersed. Journal of Higher Education and Computer Education each contributed five articles, while most journals contributed one or two. The method had migrated across disciplines rather than forming one specialized community. Primary and secondary education accounted for 41 records, higher education 40, professional or postgraduate training 21, vocational education 17, and 37 records used a general or unspecified context.

3.2 Mechanism Dimensions and Evidence

The most frequent dimension was practice and transfer (128 records), because the technique was usually embedded in a course, experiment, clinical procedure, project, or exercise. Knowledge reconstruction and simplification appeared in 47 records, and explanation or teaching output in 46. Feedback and error diagnosis appeared in 34, collaboration and role exchange in 25, and digital or AI support in 20. The pattern links application with explanation but makes the diagnostic role of an audience less consistently visible. International research links learning by teaching to explanation, feedback, and renewed application [12], while Chinese studies extend the technique to contexts such as econometrics [15].

Evidence was also uneven. Ninety-three records proposed a model, framework, or instructional pathway; 86 reported practice-based evaluation; and 42 referred to quantitative or comparative evidence. These categories overlap. A randomized neurosurgical study reported higher theory and operation scores for the Feynman group [5], whereas a pathology experiment found no significant score difference and reported greater preparation time [7]. International experiments also show that actual teaching can produce more persistent comprehension than preparation alone [6].

Table 1. Recurring internalization dimensions in 156 records (overlapping codes).

Dimension	n	Typical indicators
Practice and transfer	128	course application, experiment, procedure, new task
Knowledge reconstruction	47	simplification, mind maps, personal knowledge structures
Explanation or teaching output	46	peer teaching, microlectures, demonstrations
Feedback and error diagnosis	34	questions, correction, tests, misconception detection
Collaboration and role exchange	25	peer roles, group interaction, mutual teaching
Digital or AI support	20	platforms, MOOC, AI feedback, blended learning

4 A Six-Stage Internalization Mechanism

The first stage is selection. The learner identifies a concept, procedure, or decision that must be understood well enough to explain and use. A narrow target is important. "Understand machine learning" is not actionable; "explain why validation error rises while training error falls" can guide study and testing.

The second stage is reconstruction. Notes, diagrams, examples, code, or procedural steps are reorganized in the learner's own representation. This stage prevents explanation from becoming memorized repetition. Studies in database, data structure, and sedimentary petrology courses use mind maps, self-produced materials, and logical networks to externalize this reconstruction [1, 2]. Mind mapping has also been used to make this restructuring visible before learners return to practice [13].

The third stage is explanation. The learner teaches a peer, records a microlecture, presents a worked example, or demonstrates an operation. The audience changes the task: vague links that remain hidden during private study become visible when another person must follow the reasoning. Computer education studies have used microlectures, student-end “create-discover-discuss” activities, and course-competition integration to make knowledge output observable [1, 3, 4]. Meta-analytic evidence likewise indicates stronger gains when preparing to teach is followed by actual teaching, especially in interactive settings [14].

The fourth stage is diagnosis. Questions, errors, hesitations, failed demonstrations, or audience tests identify the boundary of current understanding. Feedback is therefore not decorative. The OBE-Feynman design for a microcontroller course assesses the explainer through the audience’s test performance, while medical training models use simulation followed by review and correction [5, 8, 9].

The fifth stage is revision. Learners return to sources, simplify unnecessary complexity, correct misconceptions, and test the explanation again. “Simplify” should not mean remove essential conditions. It means produce the shortest account that remains technically accurate and operationally useful. The recurring sequence of goal setting, simulated teaching, feedback, and concise restatement illustrates this iterative work [5, 8].

The sixth stage is transfer. Internalization becomes credible when the learner can apply the reconstructed knowledge to a new problem, not only repeat the original explanation. Practice-based studies report transfer to clinical procedures, experimental interpretation, project work, and problem solving [3-6]. Transfer also reveals overconfidence: a fluent explanation that fails under a changed condition must re-enter the cycle.

5 Discussion

The active ingredient is not speaking alone. Internalization emerges from representation, audience, feedback, revision, and transfer. Explanation without diagnosis may reward confidence; feedback without revision produces comments but no learning; simplification without transfer may yield a neat but fragile summary.

The evidence base requires caution. The analysis uses CNKI bibliographic records and abstracts, does not pool effect sizes, and includes many teaching reflections or model proposals rather than controlled experiments. Controlled studies remain a minority, samples are often modest, and outcomes vary from satisfaction to professional competence. The pathology experiment found no significant score difference but greater preparation time [7], identifying a practical cost often omitted from favorable reports.

Digital and AI tools can provide prompts, simulated audiences, feedback, and revision records, but they can also perform the explanation for the learner. Recent designs place AI between student, peer, and teacher rather than using it as an answer generator [10, 11]. The learner should first explain or predict, then use AI feedback to test and revise.

In computer experimental education, internalization should be tied to executable evidence. In performance testing, a student may justify a workload model, demonstrate a script, interpret response-time percentiles, and answer questions about bottleneck attribution. After revising a parameter or monitoring plan, the group reruns the test. Clarity matters, but so do reproducibility and evidential support.

This approach also fits project-based inquiry. The project supplies a consequential problem, while the Feynman cycle makes understanding inspectable. Tool operation without explanation is procedural familiarity; definitions without test design and verification are verbal knowledge without transfer.

6 Conclusion

The 156 CNKI journal articles show rapid growth and broad disciplinary adoption. Across varied implementations, internalization can be represented as selection, reconstruction, explanation, diagnosis, revision, and transfer. The cycle explains why presentation alone is insufficient and why evidence quality, preparation time, teacher support, and task suitability matter. In computer experiments, explanation is most credible when linked to runnable procedures, observable results, peer challenge, and repeated verification. Future research should compare process traces as well as final scores.

Acknowledgments

This study was supported by the 2024 Education and Teaching Reform Research Project of Northwest Minzu University, “Application of Project-Based Inquiry in Computer Science Experimental Teaching: A Case Study of Performance Testing and Its Tools.”

Disclosure of Interests

The author has no competing interests to declare that are relevant to the content of this article.

References

1. Zhang, S., et al.: Knowledge-output-oriented teaching based on the Feynman technique: database principles and applications. Computer Education 1, 179-183 (2025). https://doi.org/10.16512/j.cnki.jsjjy.2025.01.008
2. Xu, X., Zhu, E.: Reform and practice of practical teaching in a data structures course. Research and Exploration in Laboratory 40(9), 186-192 (2021). https://doi.org/10.19927/j.cnki.syyt.2021.09.042

3. Deng, L., et al.: A student-side Feynman-technique reform design for machine vision. Computer Education 1, 163-169 (2026). https://doi.org/10.16512/j.cnki.jsjjy.2026.01.019
4. Qi, L., et al.: MOOC, the Feynman technique, and course-competition integration in machine learning. Computer Education 6, 235-239 (2025). https://doi.org/10.16512/j.cnki.jsjjy.2025.06.017
5. Yi, D., et al.: Application of the Feynman technique in lumbar-puncture practice teaching. Chinese Journal of Clinical Neurosurgery 30(12), 755-758 (2025). https://doi.org/10.13798/j.issn.1009-153X.2025.12.012
6. Fiorella, L., Mayer, R.E.: The relative benefits of learning by teaching and teaching expectancy. Contemporary Educational Psychology 38(4), 281-288 (2013). https://doi.org/10.1016/j.cedpsych.2013.06.001
7. Huang, J., et al.: Application of the Feynman technique in pathology experimental teaching. Basic Medical Education 26(9), 765-769 (2024). https://doi.org/10.13754/j.issn2095-1450.2024.09.08
8. Wang, Y., et al.: A Feynman-technique model for CT three-dimensional post-processing training. Imaging Research and Medical Applications 10(8), 185-187 (2026). https://doi.org/10.20267/j.issn.2096-3807.2026.08.056
9. Guo, M., Wu, C.: An OBE-Feynman approach in a microcontroller course. Education and Teaching Forum 42, 89-92 (2025). https://doi.org/10.20263/j.cnki.jyjxlt.2025.42.015
10. Liu, S., Bao, B.: A vocational education model combining the Feynman technique and AI. China Modern Educational Equipment 7, 162-165 (2026). https://doi.org/10.13492/j.cnki.cmee.2026.07.033
11. Li, R., et al.: A student-peer-AI-teacher classroom driven by the Feynman technique. University Chemistry, 1-10 (online first, 2026). https://link.cnki.net/urlid/11.1815.O6.20251225.1429.002
12. Duran, D.: Learning-by-teaching: evidence and implications as a pedagogical mechanism. Innovations in Education and Teaching International 54(5), 476-484 (2017). https://doi.org/10.1080/14703297.2016.1156011
13. Hao, L., Zheng, X., Wang, P., Wang, P., Yuan, Y.: Feynman learning combined with mind mapping in clinical nursing teaching for chronic complications of diabetes. Chinese Journal of Nursing Education 20(4), 451-456 (2023). CNKI article link
14. Kobayashi, K.: Learning by preparing-to-teach and teaching: a meta-analysis. Japanese Psychological Research 61(3), 192-203 (2019). https://doi.org/10.1111/jpr.12221
15. Jia, W.: Integrating problem awareness and Feynman learning in undergraduate teaching: the case of econometrics. Journal of Higher Education 12(6), 112-116 (2026). https://doi.org/10.19980/j.CN23-1593/G4.2026.06.027