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A Cluster Study on the Translation of Teaching Functions in the Generative Artificial Intelligence Tool Ecosystem

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Abstract. As generative artificial intelligence enters the field of university teaching, most existing studies explain its educational significance from the perspectives of platform differences, task structures or risk classifications, while rarely examining how the technology is named, and paying little attention to the connection between such references and the positioning of teaching functions. This paper uses de-identified public page semantic data from six platforms provided by the research team. From 32,500 main corpus entries, the study identifies 17,380 records that contain both teaching tasks and artificial intelligence function expressions. Based on the specificity of lexical items, four mutually exclusive reference modes are established: situational, conceptual, role-based and product-based. Methods including equal-weight description, 2000-round platform-stratified cluster bootstrap, and cluster generalized estimating equations are adopted to control for platforms, five types of teaching tasks, and text length. The results show a stable positive correlation between explicit technology references and teaching assistance expressions. The adjusted odds ratios of conceptual, role-based and product-based modes are 4.622, 6.014 and 5.927 respectively. These three types of explicit references are negatively correlated with task substitution, efficiency saving and process automation. The correlation between conceptual references and content generation is sensitive to single lexical item restrictions. On this basis, the study proposes an industry-education integration curriculum path, which includes tool identification, competency audit, real task translation, process evidence design, dual-tutor review, and curriculum iteration.

Keywords: Generative Artificial Intelligence, Technology Reference, Translation of Teaching Functions, Teachers' Digital Competence, Industry-Education Integration

1. Introduction

Generative artificial intelligence is moving from single applications to continuous links of curriculum, evaluation and teachers' professional work. The*"Artificial Intelligence + Education" Action Plan* advocates promoting the integration of intelligent technology with all elements of education, and incorporates student-centered development, literacy improvement, application quality and security governance into the same institutional arrangement [1]. The *Outline for Building a Leading Country in Education (2024–2035)* states that artificial intelligence should be promoted to facilitate educational transformation [2]. In line with this, the industry-education

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integration policy requires universities to introduce enterprise technical resources, real projects and professional standards into the talent training process [3, 4]. These institutional requirements all point to a specific issue: after rapidly iterating artificial intelligence tools from enterprises are introduced into curricula, how can teachers transform technical capabilities into learnable, evaluable and reviewable teaching activities?

The framework of teachers' digital competence provides a capability coordinate for this issue. The industry standard *Teachers' Digital Literacy* incorporates digital awareness, knowledge and skills, teaching application, social responsibility and professional development into the structure of teachers' capabilities [5]. UNESCO's guidelines on generative artificial intelligence and the AI Competency Framework for Teachers further emphasize human agency, tool verification, artificial intelligence pedagogy and continuous professional learning [6, 7]. DigCompEdu also links digital resource selection, teaching orchestration, evaluation and learner support [8]. These frameworks have gone beyond the narrow view of skills that focuses only on "whether one can operate a certain tool", yet they still need to answer how the tool ecosystem is specifically connected with teaching tasks.

Domestic studies have discussed educational innovation, governance adjustment, collaborative learning and curriculum reconstruction brought by generative artificial intelligence [9-12]. International studies have also established theoretical threads such as TPACK, teachers' digital competence, Intelligent-TPACK and AI literacy [13-17]. Most relevant achievements hold that teachers should integrate technical knowledge, pedagogical knowledge, ethical judgment and situational understanding. One aspect of existing evidence has not been properly addressed: researchers generally treat "artificial intelligence" as a stable object, and rarely distinguish whether teaching functions change when it appears as an abstract concept, interactive role or specific product in educational semantics.

Technology references are not merely differences in wording. The abstract term "artificial intelligence" tends to carry macro-level judgments; role-based expressions such as "intelligent assistant" and "agent" preset interactive relationships; specific model or product names bring testable functions, versions and usage conditions into the scope of discussion. Research on task-technology fit shows that the value of technology depends on the degree of fit between task requirements and system capabilities [18]. Research on the integration of work experience in higher education also indicates that real work tasks can only form stable learning value after being organized in an educational manner [19]. Therefore, how technology is referred to may affect whether it is understood as an efficiency tool, content production tool, teaching collaborator or task substitute.

This paper takes technology reference modes as an independent analytical entry point. It focuses on three issues: first, the distribution of four types of technology reference modes in the semantic data of six platforms; second, the correlation between technology reference modes and five types of teaching functions after controlling for platforms, teaching tasks and text length, and processing relevant content in URLs; third, what testable implications this correlation can bring to the cultivation of teachers' digital competence and the curriculum design of "introducing enterprise resources into teaching". This paper does not regard semantic co-occurrence as a causal relationship, nor does it equate online expressions with teachers' actual capabilities or curriculum effectiveness.

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2. Research design

2.1. Data source, audit and sample formation

The data are sorted from publicly accessible page semantic records on Bilibili, Douyin, Kuaishou, Weibo, Xiaohongshu and Zhihu. The main corpus contains 32,500 records, and another 3,000 records are marked with clear risk enhancement purpose labels and fixed platform quotas. This paper retains records that contain at least one teaching task lexical item and at least one artificial intelligence function lexical item, forming 17,380 analysis samples associated with 300 source URLs, with 50 URLs per platform. The number of records per platform is 3,772 for Bilibili, 3,317 for Douyin, 2,635 for Kuaishou, 1,192 for Weibo, 3,106 for Xiaohongshu, and 3,358 for Zhihu. The unit of analysis is semantic records, and the unit of clustering is source URLs. The number of records cannot be interpreted as the number of independent users, nor can the platform distribution be interpreted as a probability sample.

2.2. Technology reference modes, teaching tasks and function coding

This paper establishes four mutually exclusive technology reference modes according to the information specificity of explicit lexical items. The classification follows the operation rule: "product-based takes precedence over role-based, role-based takes precedence over conceptual, and records without explicit lexical items are classified as situational". This rule only serves semantic coding and does not represent technology maturity, educational value or product quality. This paper does not compare manufacturers, countries or brand levels, nor does it regard the occurrence of product names as actual usage. Table 1 lists the complete rules.

Table 1. Operational definitions of technology reference modes

Mode	Determination Rule	Key Lexical Items	Analytical Implication
Situational	No explicit artificial intelligence lexical items in the field	None	The source context and teaching functions jointly indicate the topic of artificial intelligence, but the text does not explicitly name the technology
Conceptual	Only abstract technical concepts appear	AI, artificial intelligence, AIGC, generative AI, large model, LLM	Organizes educational judgments by general technology categories
Role-based	Interactive role lexical items appear and no specific product words	Intelligent assistant, AI assistant, chatbot, Agent	Organizes human-machine relationships by assistance, dialogue or action roles
Product-based	At least one specific model or product name appears	Tongyi, Wenxin, GPT, Xinghuo, Kimi, DeepSeek, ChatGPT, Claude, Gemini, etc.	Organizes function judgments by identifiable tools or models

Note: A unique mode is assigned in the order of product-based, role-based and conceptual

Five types of teaching tasks and five types of artificial intelligence functions are established. Teaching tasks include teachers' teaching and professional development, students' learning and tutoring, classroom and curriculum implementation, homework writing and practice, and examination assessment and feedback. Artificial intelligence functions include efficiency and resource saving, content generation and processing, process automation, teaching assistance and

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collaboration, and task substitution. Both tasks and functions adopt multi-label coding, and one record can fall into multiple task domains or function domains. The research team does not supplement the implied meaning of the original text, nor does it use user identity, geographic location or personal profiles to assist classification.

2.3. Statistical strategy

This paper first calculates the record-weighted proportion, and then calculates the proportion of reference modes by treating each source URL as equal weight. For the URL-equal-weight results, a 2000-round platform-stratified cluster bootstrap is used to estimate the 95% confidence interval. Then this paper takes five types of artificial intelligence functions as binary dependent variables respectively, and fits five logit-link generalized estimating equations according to the population-averaged estimation framework. The model sets source URLs as clustering units, adopts an exchangeable working correlation structure and robust standard errors. The model simultaneously controls for three types of explicit reference dummy variables, five types of teaching tasks, five platform dummy variables, and standardized text length. Bilibili and situational reference serve as the platform and reference baseline respectively.

$$logitPr(Y=1)=\beta_0+\beta^\top M+\gamma^\top T+\delta^\top P+\eta L \tag{1}$$

In Equation (1), Y indicates whether a certain type of teaching function appears; M, T and P represent vectors of three types of explicit references, five types of teaching tasks and five platform control items respectively; L represents standardized text length. The model is estimated separately for each type of teaching function, with record i nested in source URL u. This paper applies Benjamini-Hochberg false discovery rate correction to 15 reference mode coefficients, and reports odds ratios, 95% confidence intervals and corrected q-values.

$$p_c=\frac{1}{U}\sum_{u=1}^{U}\frac{1}{n_u}\sum_{i=1}^{n_u}I(M_{iu}=c) \tag{2}$$

In Equation (2), p_c is the URL-equal-weight proportion of reference mode c, U is the total number of source URLs, n_u is the number of records in URL u and $I(\cdot)$ is the indicator function. The URL-equal-weight proportion is used to reduce descriptive bias caused by different record volumes of individual pages. Robustness checks include an independent working correlation structure, samples retaining only single AI lexical items or no AI lexical items, and leave-one-platform-out repeated estimation. This paper treats these analyses as correlation tests and does not conduct causal identification.

2.4. Data protection

The research data do not include usernames, account IDs, private message content, location information, contact details, user profiles or other non-public information, nor do they display verbatim original text, original links or precise timestamps. The data minimization approach, purpose limitation measures, de-identification procedures and aggregated reporting practices adopted in this paper follow internet research ethical guidelines, and are consistent with the protective principles in the *Personal Information Protection Law*, *Data Security Law* and GDPR.

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3. Research results

3.1. Overall distribution of technology reference modes

Among the 17,380 records, situational references account for 48.36%, product-based references 32.58%, conceptual references 10.87%, and role-based references 8.18%. After equal-weight processing by URL, the proportions of the four types become 47.01%, 33.23%, 11.22% and 8.54% respectively, and this order is consistent with the record-weighted results. Product-based references have become the main component of explicit technical expressions, yet nearly half of the records still rely on the source context and do not explicitly name the technology. Table 2 also presents the record proportions of five types of functions within each mode.

Table 2. Distribution of technology reference modes and function proportions within modes

Reference Mode	n (Record Proportion)	URL-Equal-Weight Proportion [95% CI]	Efficiency Saving	Content Generation	Process Automation	Teaching Assistance	Task Substitution
Situational	8405(48.36%)	47.01% [45.92, 48.11]	48.17%	36.84%	19.88%	10.89%	17.98%
Conceptual	1890(10.87%)	11.22% [10.53, 11.93]	32.01%	47.46%	14.55%	33.39%	12.80%
Role-based	1422(8.18%)	8.54% [7.81, 9.36]	37.55%	29.47%	15.82%	38.05%	14.98%
Product-based	5663(32.58%)	33.23% [32.12, 34.36]	36.41%	29.49%	16.86%	37.10%	14.97%

Note: The proportions of the five functions are the record proportions within the corresponding reference mode. Functions adopt multi-label coding, so the sum of proportions in a row can exceed 100%; URL intervals are derived from 2000-round platform-stratified cluster bootstrap.

Unadjusted within-mode proportions show differences. Among situational records, efficiency saving accounts for 48.17%, while teaching assistance only makes up 10.89%. Among conceptual, role-based and product-based records, teaching assistance reaches 33.39%, 38.05% and 37.10% respectively. The task substitution proportions of these three types of explicit references are all lower than that of the situational type. Descriptive results show that when technology names or interactive roles enter the text, the focus of discussion leans more toward "how to assist teaching" rather than broad content such as time saving, automation or substitution.

3.2. Adjusted correlation between technology reference modes and teaching functions

Table 3 presents the core coefficients of the URL-cluster generalized estimating equations. The joint Wald tests of reference modes for all five models reach statistical significance, and the q-values of all 15 mode coefficients are less than 0.001 after false discovery rate correction. The most stable results appear in the two functions of teaching assistance and task substitution. Compared with the situational type, the adjusted odds ratios of conceptual, role-based and product-based references for teaching assistance are 4.622, 6.014 and 5.927 respectively. The odds ratios of the same three modes for task substitution are 0.617, 0.717 and 0.700.

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Table 3. URL-cluster GEE results of technology reference modes and five types of teaching functions

Teaching Function	Conceptual OR [95% CI]	Role-based OR [95% CI]	Product-based OR [95% CI]	Joint Wald $\chi^2(3)$
Efficiency and Resource Saving	0.468 [0.416, 0.526]	0.571 [0.502, 0.651]	0.538 [0.500, 0.580]	322.33***
Content Generation and Processing	1.446 [1.305, 1.603]	0.636 [0.558, 0.725]	0.621 [0.571, 0.676]	302.75***
Process Automation	0.663 [0.570, 0.772]	0.709 [0.606, 0.831]	0.754 [0.681, 0.835]	46.14***
Teaching Assistance and Collaboration	4.622 [3.958, 5.397]	6.014 [5.190, 6.968]	5.927 [5.145, 6.829]	727.52***
Task Substitution	0.617 [0.534, 0.712]	0.717 [0.619, 0.829]	0.700 [0.630, 0.777]	72.80***

*Note: The reference group is situational reference. The model controls for five types of teaching tasks, platforms and standardized text length, with source URLs as clustering units and robust standard errors; *** indicates $p<0.001$ for the joint test. All 15 mode coefficients have $q<0.001$ after Benjamini-Hochberg correction.*

Efficiency saving and process automation show consistent direction in results. The odds ratio of conceptual reference for efficiency saving is 0.468, and for process automation is 0.663. The odds ratio of role-based reference for efficiency saving is 0.571, and for process automation is 0.709. The odds ratio of product-based reference for efficiency saving is 0.538, and for process automation is 0.754. Explicit naming does not push semantics toward a stronger "automatic completion" narrative, but appears together with fewer efficiency-oriented and procedural expressions.

Content generation and processing require separate explanation. In the main model, the odds ratio of conceptual reference is 1.446, while those of role-based and product-based are 0.636 and 0.621 respectively. This result does not form a continuous structure from abstract to concrete, and the conceptual coefficient changes direction in the single-AI-lexical-item sample. Based on this, this paper only regards the main model result as a combined feature within the sample, and does not judge that conceptual references can naturally promote content generation based on this.

3.3. Robustness checks

The mode odds ratios obtained from the independent working correlation structure are similar to those of the main model. After retaining only single AI lexical items or no AI lexical items, the sample size is 13,915. The odds ratios of the three types of explicit references for teaching assistance are 5.785, 6.090 and 5.763 respectively, and for task substitution are 0.750, 0.799 and 0.770 respectively. Efficiency saving and process automation also maintain the trend of being lower than 1. The odds ratio of conceptual reference for content generation changes from 1.446 in the main model to 0.647, indicating that this result is affected by the multi-item co-occurrence structure.

After removing platforms one by one, the odds ratios of conceptual, role-based and product-based references for teaching assistance fall within the ranges of 3.82–5.46, 5.10–7.01 and 5.03–7.17 respectively, and all ranges for task substitution remain below 1. The robustness results support the core judgment that "explicit references are closer to teaching assistance and less close to task substitution", but do not support an equally strong interpretation of the relationship with content generation.

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4. Discussion

4.1. Technology references bring testable specificity to teaching functions

The main finding of this paper is not that product-based modes are necessarily better than conceptual or role-based modes. The odds ratios of role-based and product-based modes for teaching assistance are similar, and all three types of explicit references have lower associations with efficiency saving, process automation and task substitution. The results more support a "teaching concretization" explanation: when the text explicitly mentions technology categories, interactive roles or specific products, discussants are more likely to place artificial intelligence in relationships of assistance, feedback and joint completion; when the technology name is missing, the text is more likely to stay on broad functions such as time saving, automation or substitution.

This structure expands the unit of analysis for artificial intelligence education research. Existing studies often discuss tool capabilities, teacher knowledge and curriculum tasks separately [20]. This paper points out that technology references themselves can serve as an intermediate part connecting the three. Specific names make tool versions, available functions and usage conditions easier to verify; role-based names make interaction methods easier to discuss; abstract concepts are suitable for carrying overall judgments. Only when curriculum teams transform these semantic levels into functional tests and task descriptions can technology names have educational significance.

4.2. Teachers' digital competence should advance from tool operation to tool ecosystem audit

The realistic environment teachers face is not stable tools, but constantly updated models, interfaces, licensing conditions and data processing methods. If teacher training only revolves around single product demonstrations, knowledge will quickly become invalid due to version changes. The results of this paper show that teachers' digital competence should include at least five observable capabilities: the ability to identify tool categories and versions, the ability to verify function claims and actual outputs, the ability to map technical capabilities to learning tasks, the ability to design process evidence and verify procedures, and the ability to revise usage rules based on curriculum data.

These five capabilities are consistent with the core requirements of teachers' digital literacy, DigCompEdu and Intelligent-TPACK [5, 8, 14, 15], but this paper further organizes them into a work chain in curricula. Teachers do not need to master all operations of all models, but should establish cross-tool comparison criteria. For example, teachers can compare the factual accuracy, citation traceability, feedback quality, data processing requirements and students' cognitive engagement of different tools through the same professional task, and then decide which teaching link the tool should enter. Such comparison can transform "tool proficiency" into "teaching judgment ability".

4.3 Curricula of "Introducing Enterprise Resources into Teaching" Need to Establish a Repeatable Technology Translation Process

Based on the correlation between technology references and teaching functions, this paper proposes an organizational path that can be tested in curriculum practice. As shown in Figure 1, the process of enterprise technical resources entering curricula is divided into six consecutive links.

First, establish a tool ecosystem inventory. Enterprise tutors provide production scenarios, commonly used tools, post standards and quality requirements, and university teachers record versions, data requirements, licensing conditions and alternative solutions. The inventory is not equivalent to a recommendation list, and the curriculum team needs to regularly review tool

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changes. Second, enterprise tutors and university teachers conduct a competency audit. Both parties use the same set of professional tasks to test output accuracy, stability, interpretability, data protection and professional compliance, avoiding setting teaching uses directly based on product promotion. Third, university teachers translate enterprise tasks into learning tasks. Teachers need to clarify learning objectives, prerequisite knowledge, stages where artificial intelligence is allowed, judgments that students must complete independently, and evaluation evidence. Enterprise projects can retain real constraints, but teachers must adjust task scale, data complexity and feedback rhythm so that students can form professional understanding within curriculum time. Fourth, the curriculum team designs process evidence. Students submit prompt records, data sources, key versions, revision reasons, manual verification statements and oral defenses, based on which teachers judge whether students understand and undertake key decisions. Fifth, dual tutors conduct joint review. Enterprise tutors mainly check professional standards, industry constraints and result usability; university teachers mainly check learning objectives, cognitive engagement and evaluation fairness. The two types of judgments cannot replace each other. Sixth, the curriculum team iterates the tool inventory and task arrangements based on student works, error types, usage logs and tutor evaluations. This closed loop enables enterprise technology supply to enter talent training after educational processing, and also enables teachers' digital competence to gain evidence in real curriculum improvement.

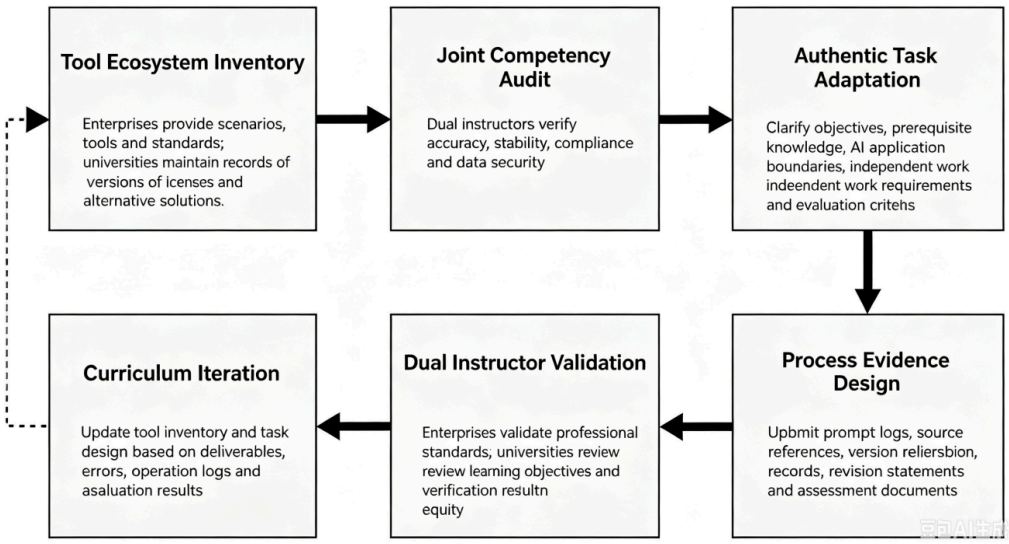


Figure 1. Artificial intelligence teaching translation path for curricula of "introducing enterprise resources into teaching"

5. Conclusion

This paper takes technology reference modes as the unit of analysis, and tests 17,380 semantic records from six platforms to explore the relationship between the generative artificial intelligence tool ecosystem and the positioning of teaching functions. The test results show that situational references account for nearly half of the total, and product-based references have become the main form of explicit expression. After controlling for platforms, teaching tasks and text length, conceptual, role-based and product-based references all show a positive correlation with teaching assistance, and a negative correlation with efficiency saving, process automation and task substitution. Based on the research results, teachers' digital competence is summarized into tool

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identification, competency audit, task translation, evidence verification and professional inquiry, and a path of "introducing enterprise resources into teaching" is proposed: "tool ecosystem – competency audit – real task translation – process evidence – dual-tutor review – curriculum iteration". The value of this path lies not in increasing the number of tools, but in transforming enterprise technical resources into evaluable learning tasks.

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