Innovative Research on Foreign Language Talent Cultivation Models in the Era of "New Quality Productive Forces"

Yafei Wu[1]

[1] *Guangzhou Nanfang College, Guangzhou, China*
[1]*Correspoding author. Email: wuyf@nfu.edu.cn*

ABSTRACT
Artificial intelligence and digital technologies are changing both the organization of work and the skills expected of university graduates. In China, these changes are increasingly discussed through the concept of New Quality Productive Forces (NQPF), which emphasizes innovation, digital transformation, and higher-quality development. For foreign language programs in applied universities, the challenge is therefore not simply to add AI tools to existing courses. It is to reconsider what students should be able to do with language, disciplinary knowledge, and digital technologies when they enter the workplace. Taking the Guangdong-Hong Kong-Macao Greater Bay Area (GBA) as its regional context, this paper develops a conceptual model for foreign language talent cultivation based on Outcome-Based Education (OBE). The model gives particular attention to three connected issues: curriculum restructuring around workplace outcomes, the development of digital intelligence literacy through human-machine collaboration, and the use of data-informed teaching management to support continuous improvement. Rather than treating technology as a substitute for language learning, the paper argues that AI should be used where it can extend practice, feedback, analysis, and productivity, while human judgment remains central to cultural interpretation, critical evaluation, and professional communication. The proposed framework is intended as a practical reference for applied universities seeking closer alignment between foreign language education, regional industry needs, and the ongoing digital transformation of higher education.

Keywords: *New quality productive forces, Digital intelligence literacy, Human-machine collaboration, Outcome-based education; industry-education integration; applied universities; higher education digital transformation*

1. INTRODUCTION

1.1 The Intersection of Macroeconomic Evolution and Digital Education Strategies

The expansion of generative artificial intelligence, data-intensive production, and digitally networked services is reshaping the way economic value is created. In China, the term New Quality Productive Forces has been used to describe a shift toward productivity driven more strongly by technological innovation, new combinations of production factors, and industrial upgrading [1]. The concept is macroeconomic in origin, but its implications extend directly to higher education. Universities are expected to prepare graduates for workplaces in which routine tasks are increasingly automated and where professional value depends on the ability to combine disciplinary knowledge with judgment, communication, and digital competence.

This change is particularly visible in applied higher education. Traditional measures of educational input—course hours, content coverage, or the number of modules completed—do not by themselves show whether graduates can solve problems in realistic settings. A foreign language student, for example, may perform well in grammar, reading, or translation exercises but still find it difficult to handle a multilingual project, evaluate an AI-generated translation, communicate with a

client, or explain a culturally specific concept to an overseas audience. Under an NQPF-oriented view of talent development, such practical performance becomes more important because the workplace increasingly rewards the integration of knowledge rather than the possession of isolated knowledge units.

At the same time, national education policy is placing digital transformation closer to the center of teaching reform. The 2026 Action Plan for "Artificial Intelligence + Education," jointly issued by five national agencies, calls for deeper integration of AI across educational elements, processes, and scenarios [2]. The policy direction does not imply that technology should replace established disciplinary foundations. Instead, it raises a more difficult question: which parts of teaching should be supported by technology, and which capabilities still require sustained human training? For foreign language education, this distinction matters because machine translation and large language models can perform many routine language tasks quickly, while responsible use still requires human evaluation of context, cultural appropriateness, factual accuracy, and communicative purpose [6][8][16][17].

The resulting pressure on foreign language programs is therefore twofold. Programs need to protect the disciplinary core of language competence, linguistic awareness, and intercultural communication, while also creating opportunities for students to use these capabilities in digitally mediated professional tasks. Reform becomes less a matter of adding one or two technology courses and more a matter of redesigning the relationship among language learning, disciplinary knowledge, workplace practice, and AI-supported work.

1.2 Research Objectives and Regional Context

This paper examines how applied universities can reconstruct foreign language talent cultivation in response to NQPF and the digital transformation of education. It is a conceptual and policy-oriented study rather than an empirical impact evaluation. Drawing on current scholarship on AI competency, constructive alignment, work-integrated learning, and learning analytics [4][10][14][18], it proposes a framework that links graduate outcomes to curriculum design, classroom practice, industry participation, and teaching management.

The Guangdong-Hong Kong-Macao Greater Bay Area provides the regional setting for the discussion. The region's official development plan gives particular attention to innovation and technology, a modern industrial system, international trade and services, tourism, and cross-border cooperation [7]. In such an environment, employers may need graduates who can move between language work and domain-specific tasks rather than perform language conversion alone. The paper therefore asks three practical questions: What competencies should an applied foreign language graduate possess? How can curriculum and assessment be organized around those competencies? And how can AI be incorporated without weakening the human abilities that give language professionals their distinctive value?

2. LITERATURE REVIEW

2.1 Academic Discourse on New Quality Productive Forces and the Limits of Traditional Models

Recent work on NQPF-oriented foreign language education emphasizes innovation, interdisciplinary integration, and closer links between language education and technological and professional change [1][3]. Zheng and Gao further argue that "new quality foreign language education" should retain the practical, cultural, and humanistic foundations of language learning [11]. Much of this discussion, however, remains conceptual or policy-oriented. There is still less detail on how a specific humanities discipline should translate these macro-level expectations into teachable outcomes, course structures, and assessment practices.

Foreign language education has already experienced several rounds of pedagogical change. Grammar-translation traditions were challenged by communicative approaches, and later by task-based learning, content-based instruction, and other approaches that place greater emphasis on use. Yet curriculum structures in many institutions still divide language learning into relatively stable subject blocks such as reading, writing, linguistics, literature, and translation. These components remain academically valuable, but when they operate independently of professional contexts, students may have limited opportunities to integrate what they know in a realistic task.

The spread of neural machine translation and large language models has made this structural

issue more visible. Routine translation, drafting, summarization, and basic language correction can now be completed with substantial technological assistance. A systematic review of neural machine translation in language teaching shows that the technology can support learning but also changes the kinds of knowledge and monitoring strategies learners need [6]. The appropriate response is not to abandon linguistic training. On the contrary, reliable use of AI often depends on stronger language awareness, because students need enough linguistic and contextual knowledge to detect errors, omissions, register problems, and misleading fluency.

For this reason, the central weakness of the traditional model is better described as fragmentation than as simple obsolescence. Language, disciplinary knowledge, digital tools, and workplace practice are too often taught in separate spaces. An NQPF-oriented model needs to bring these elements into the same learning tasks so that students learn to mobilize them together.

2.2 Digital Intelligence Literacy and Human-Machine Collaboration

AI literacy has become an important strand of recent educational research. Existing frameworks usually go beyond operational skills and include understanding what AI can and cannot do, evaluating outputs, recognizing bias and ethical risks, and using AI responsibly in context [4][9]. A systematic review of AI in higher education also documents the rapid expansion of AI-related research and applications across university settings [5]. For foreign language students, this broader definition is useful because fluent machine output can easily create an illusion of correctness. Students therefore need the capacity to question an answer that sounds natural but may be inaccurate, culturally inappropriate, or poorly matched to the communicative purpose.

The same issue applies to teachers. If AI is used only to generate exercises or shorten preparation time, its pedagogical contribution remains limited. Teachers also need to decide when AI-generated feedback is appropriate, how students should disclose or document AI use, and which learning outcomes should be assessed without technological assistance. These decisions require pedagogical judgment rather than technical familiarity alone.

Human-machine collaboration offers a productive way to frame this relationship. Instead of asking whether AI should replace a particular language task, the focus shifts to task allocation. Machines are efficient at producing variants, processing large amounts of text, and giving rapid preliminary feedback. Human learners are still responsible for purpose, interpretation, source checking, cultural judgment, ethical decisions, and final accountability. Studies of generative AI in language education increasingly support this complementary view, while also noting the need for structured guidance and critical evaluation [8][16][17]. What remains less developed is an institutional model that connects such classroom practices with curriculum outcomes and program-level quality assurance.

3. NEEDS ANALYSIS AND PARADIGM SHIFT

3.1 Regional Industrial Demands and the Evolving Competency Profile

The GBA is a useful context in which to examine changing expectations for foreign language graduates. Its development plan prioritizes innovation and technology, modern industries, international trade and services, and deeper cooperation among Guangdong, Hong Kong, and Macao [7]. In these settings, language is rarely used in isolation. A graduate may need to prepare bilingual materials for a technology product, localize digital content, communicate with overseas clients, support an international exhibition, interpret technical information, or adapt a message for a different cultural audience. Each task requires language competence, but none can be completed well through language knowledge alone.

This suggests a shift from a single-skill profile to a layered competency profile. The first layer remains linguistic: graduates need strong comprehension, expression, translation, and intercultural communication. The second layer is domain-related. Students should be able to learn the terminology, conventions, and basic operational logic of the sector in which they work. The third layer is digital. Graduates should know how to use AI and other digital tools to search, draft, compare, localize, and analyze information, while checking the reliability of machine output. The fourth layer is professional: collaboration, problem solving, audience awareness, and ethical responsibility become essential because many real tasks are project-based and involve multiple stakeholders.

The growth of generative AI makes this layered profile more urgent. It reduces the value of some repetitive tasks but increases the value of monitoring, editing, and decision-making. A student who simply accepts an AI translation has not demonstrated professional competence; a student who can explain why a translation is unsuitable for a particular market, revise it, verify terminology, and justify the final choice has. AI literacy research similarly stresses evaluation and responsible use rather than simple access to tools [9].

For applied universities, the implication is practical. Curriculum reform should begin with the work students are expected to perform after graduation and then identify the knowledge and practice needed to reach that level. This is the point at which OBE becomes especially relevant.

3.2 The Outcome-Based Education Paradigm Shift and Model Comparison

Outcome-Based Education starts from what learners should be able to demonstrate at the end of a program and works backward to curriculum, teaching, and assessment. This logic is closely related to constructive alignment: learning outcomes, learning activities, and assessment should point in the same direction [10]. For foreign language education, the advantage of this approach is that it can connect academic content with observable professional performance without reducing education to short-term vocational training.

A program might, for example, define an outcome such as 'students can produce and revise multilingual content for a specified international audience using appropriate digital tools and documented quality-control procedures.' Such an outcome immediately affects the curriculum. Students need language and intercultural knowledge, but they also need repeated project practice, feedback, tool literacy, and explicit criteria for quality. Assessment can then examine the final product, the reasoning behind revisions, the use of sources, and the student's ability to explain the role of AI in the process.

OBE also creates a mechanism for periodic adjustment. If graduates or industry partners report that students lack oral interaction, localization, data handling, or quality-control skills, the program can trace the problem back to specific learning outcomes and course activities. This makes reform more manageable than adding new courses whenever a new technology appears. The goal is not constant expansion of the curriculum but better alignment among outcomes, content, practice, and evidence of learning [10].

“Table 1” summarizes the main differences between a conventional content-centered model and the model proposed in this paper. The contrast is intentionally functional rather than absolute: traditional components such as literature, linguistics, and translation theory remain important where they contribute to program outcomes. The proposed change concerns how these components are connected to application, digital work, and assessment.

Table 1. Comparative analysis of talent cultivation models

Cultivation Dimension	Traditional Foreign Language Model	NQPF-Driven, OBE-Oriented Model
Core Objective	Emphasis on linguistic knowledge, literature, and routine translation skills.	Integrated language, intercultural, digital, and industry-oriented competence.
Curriculum Structure	Discipline-based courses with relatively fixed boundaries.	Modular pathways linking language learning with digital tools and professional contexts.
Pedagogical Approach	Teacher-led instruction with substantial emphasis on content transmission.	Learner-centered and project-based learning with guided human-machine collaboration.
Role of Technology	Mainly auxiliary: information search, word processing, audio/video, or isolated tools.	Embedded selectively in learning tasks for drafting, analysis, feedback, comparison, and quality control.
Assessment Strategy	Primarily summative tests of knowledge and language accuracy.	Multiple forms of evidence including authentic tasks, process records, reflection, and outcome attainment.
Industry Integration	Often concentrated in short internships or final-year practice.	Sequenced work-integrated learning, enterprise-informed tasks, mentors, and authentic projects.

4. INNOVATIVE CULTIVATION STRATEGIES

4.1 OBE-driven Curriculum Reconstruction and Industry-Education Integration

Curriculum reconstruction should begin with a small set of program-level outcomes rather than with a list of fashionable technologies. For applied foreign language programs in the GBA, these outcomes may include advanced language use, intercultural communication, industry-oriented communication, digital intelligence literacy, collaborative project work, and the ability to evaluate AI-assisted output. Recent NQPF-oriented research on innovative foreign language talent cultivation likewise stresses practical pathways that connect foreign language education with emerging professional needs [12]. Courses can then be mapped against these outcomes so that gaps and unnecessary duplication become visible.

A modular structure is useful because it allows programs to preserve a common language foundation while offering different application pathways. After core training, students could move into clusters such as international business communication, international communication and content localization, culture and tourism communication, or AI-assisted language services. The exact labels will vary by institution, but the design principle is the same: each pathway should combine language practice with a recognizable professional context and should culminate in tasks that resemble real work rather than disconnected classroom exercises.

AI-related content should also be distributed across the curriculum instead of being confined to a single 'AI course.' In writing, students can compare human and AI drafts; in translation, they can conduct post-editing and terminology checks; in interpreting or speaking courses, conversational systems can provide additional rehearsal; in international communication, students can test how the same message changes across audiences and platforms. Research on intelligent writing assistance suggests that these tools are most useful when learners remain active decision-makers rather than passive recipients [13].

Industry-education integration is needed to make these tasks credible. Work-integrated learning research shows that different forms of workplace exposure contribute differently to employability, which means that internships alone are not a sufficient solution [14]. Programs should therefore build a sequence of practice: short authentic tasks in lower years, project collaboration with external partners in the middle of the program, and more sustained internships or capstone projects later. Enterprise mentors can contribute briefs, terminology, feedback, and evaluation criteria even when they are not directly involved in weekly teaching.

This arrangement also reduces a common problem in university-enterprise cooperation: the partnership exists administratively but has little effect on what students actually learn. The stronger form of integration is curricular. Industry input should influence task design and assessment evidence, while universities retain responsibility for educational quality, language development, ethics, and transferable learning.

4.2 Systematic Development of Digital Intelligence Literacy and Human-Machine Collaboration

Digital intelligence literacy should be treated as a progression rather than a one-time skill. At an introductory level, students need to understand the basic affordances and limits of generative AI, machine translation, speech technologies, and data tools. At an intermediate level, they should learn to formulate useful prompts, compare outputs, verify information, manage terminology, and document revisions. At an advanced level, students should be able to select tools strategically, explain the risks of a workflow, and take responsibility for the final communicative product. UNESCO's AI competency frameworks for teachers and students provide a useful reference for this progression because they connect technical use with human agency, ethics, and critical judgment [4][15].

In language courses, the most important principle is that AI use should create more opportunities for thinking, not fewer. One practical pattern is generate–evaluate–revise–justify. Students first use an AI system to produce a draft or alternative versions. They then identify problems, revise the text, and explain the reasons for important changes. This simple sequence changes the task from output production to informed decision-making. It can be used in translation, writing, localization, advertising, tourism communication, or other applied contexts [16].

A second pattern is comparison across sources or systems. Students may compare a machine translation with a published translation, compare responses from two models, or compare an AI-generated cultural explanation with authoritative background material. The learning objective is not to determine which system is 'best' in the abstract. It is to develop criteria: accuracy, register, terminology, audience fit, cultural completeness, and factual reliability. Such criteria make the student's reasoning visible and therefore assessable.

Teachers need corresponding professional development. They should be able to design AI-supported tasks, set disclosure rules, distinguish acceptable assistance from unacceptable substitution, and assess process as well as product. They also need confidence in identifying situations in which AI should not be used, for example when a task is intended to measure unaided oral performance or foundational language knowledge. Human-machine collaboration works only when the division of labor is explicit.

The teacher's role consequently shifts but does not diminish. When students can obtain instant drafts and explanations, classroom value increasingly lies in task design, diagnosis, feedback, discussion, and standards of quality. The teacher becomes the person who creates conditions in which students learn to interrogate machine output rather than simply consume it. This interpretation is consistent with research that describes the relationship between teachers and large language models as complementary rather than substitutive [17].

4.3 Constructing an Intelligent Teaching Management Ecology

Curriculum and classroom reform are difficult to sustain if program management still relies almost entirely on end-of-semester scores and occasional curriculum reviews. An intelligent teaching management ecology should therefore be understood as a quality-assurance system that connects learning outcomes, course evidence, student performance, and external feedback. The emphasis should be on useful evidence, not on collecting as much data as possible.

A practical system could combine several types of evidence: course-level attainment of program outcomes, student performance on authentic projects, feedback from internships or enterprise mentors, student self-reflection, and selected learning-process data from digital platforms. Learning analytics research shows that data are most useful when they are linked to an instructional response rather than displayed only on dashboards [18][19]. The same principle should guide program management. If a particular outcome is consistently weak, the question is not simply how to visualize the problem but what change in curriculum, task design, or support is warranted.

This also argues for a cautious approach to prediction. Predictive models may help identify patterns, but they should not replace teacher judgment or become opaque mechanisms for labeling students. In language education, performance is context-sensitive, and qualitative evidence often matters. A student's ability to explain a translation choice, respond to a client, or repair a misunderstanding may be more informative than a single numerical indicator. An intelligent system should therefore combine quantitative and qualitative evidence and keep academic staff involved in interpretation.

At the program level, the OBE cycle can be organized around four stages. First, the institution identifies external demands and defines graduate outcomes. Second, courses and projects are mapped to those outcomes. Third, evidence is collected from student work and relevant stakeholder feedback. Fourth, the program uses the evidence to revise outcomes, content, or assessment where necessary. Learning analytics dashboards can support this cycle if they are designed around pedagogical questions rather than around data display for its own sake [20].

“Figure 1” summarizes the proposed relationship among the external environment, OBE outcomes, pedagogical and technological tracks, the learning environment, and the continuous-improvement loop. The model is deliberately cyclical. Employment and stakeholder feedback return to the beginning of the process so that program objectives can be reconsidered as industry practices and technologies change.

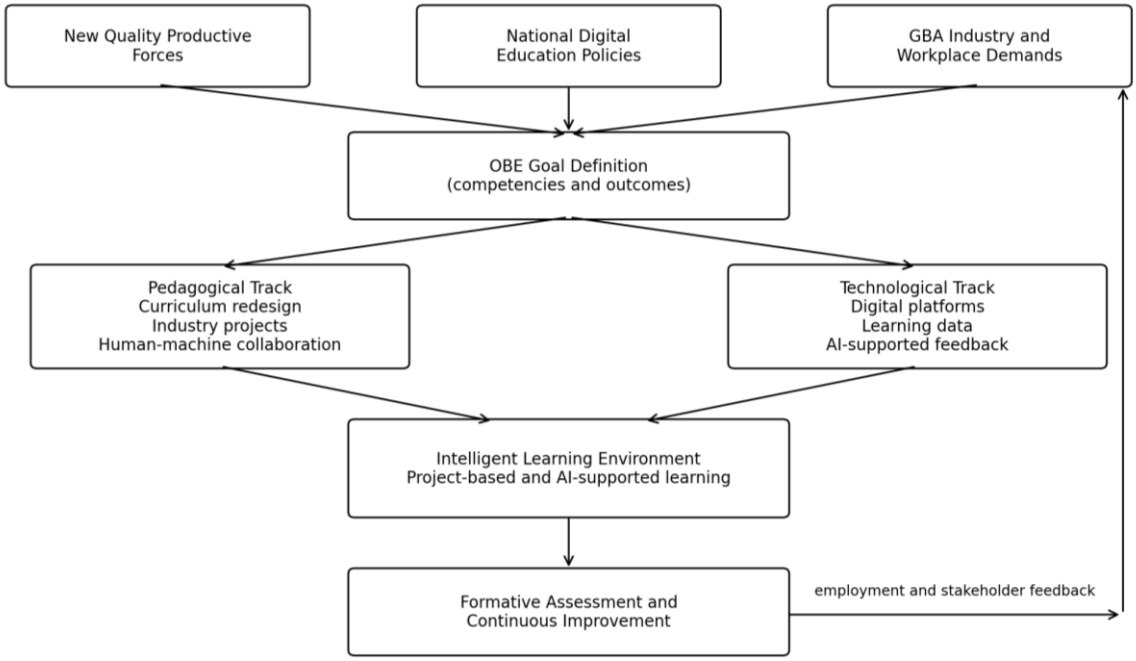


Figure 1 OBE-oriented intelligent teaching and management ecology.

5. CONCLUSION

The emergence of NQPF and the rapid spread of AI do not make foreign language education less important; they change the conditions under which language expertise is valuable. Routine linguistic production can increasingly be assisted by machines, while effective professional communication still depends on context, audience awareness, cultural interpretation, verification, and responsibility. Applied universities therefore need a model that retains disciplinary depth but gives students more opportunities to use language in complex, technology-mediated situations.

This paper has proposed an OBE-oriented framework built around three connected reforms. The first is curriculum alignment: program outcomes should define the competencies students are expected to demonstrate, and courses should be organized to support those outcomes through progressively more authentic tasks. The second is digital intelligence literacy: AI should be integrated across language learning as an object of critical use, not treated as a shortcut or a separate technical add-on. The third is management and quality assurance: evidence from courses, projects, workplace learning, and stakeholder feedback should feed into a continuous improvement cycle.

The framework also clarifies the role of human-machine collaboration. In a foreign language program, the question is not whether students should use AI, but how they should use it and what remains their responsibility. AI can expand practice, generate alternatives, and accelerate routine processing; students must still evaluate meaning, verify facts and terminology, adapt communication to audiences, and justify final decisions. This division of labor provides a more durable educational principle than training students on any single platform.

Several limitations should be noted. The model is conceptual and has not yet been tested through longitudinal student data or comparative program evaluation. Its regional discussion is centered on the GBA, and implementation will vary according to institutional resources, student profiles, and local industry structures. Future research should therefore examine how specific elements of the model affect language performance, AI literacy, project competence, and graduate outcomes over time. Such evidence would help determine which parts of the proposed framework are transferable across different types of universities and which require local adaptation.

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