



Research on the Empowering Role of Digital-Intelligence Technologies in Personalized Learning for Beginner-Level International Students of Chinese

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Abstract: Against the backdrop of the continuous integration of digital-intelligence technologies into educational practice, beginner-level Chinese language learning has exhibited a parallel trend toward platformization and personalization. Based on questionnaire data and statistical analysis of international students at local universities in Yunnan Province, this study systematically examines the current application status and structural characteristics of digital-intelligence technologies in personalized learning for elementary Chinese. The findings indicate that digital-intelligence tools demonstrate a relatively high level of adoption and are positively perceived by learners. They provide significant support particularly in vocabulary consolidation and listening training. However, several challenges remain, including an overemphasis on basic language skills, fragmented platform usage, and insufficient perceived personalization support. In response, this study proposes optimization strategies from three dimensions: the integration of comprehensive language competencies, the systematization of learning pathways, and the construction of data-driven regulation mechanisms, with the aim of promoting the structural development and sustained enhancement of language proficiency.

Keywords: Digital-Intelligence Technologies; Elementary Chinese Teaching; Personalized Learning; International Chinese Education

1. Introduction

Language is widely regarded as a fundamental tool for human communication, a carrier of civilization, and a bridge for enhancing mutual understanding. In the context of International Chinese Education, strengthening this field is considered essential for promoting mutual learning among civilizations and contributing to the development of a community with a shared future for humanity. Against the backdrop of the continued advancement of the Digital China initiative and the national strategy for educational digitalization, International Chinese Education, as an important support system for China's opening-up and the Belt and Road Initiative, not only fulfills the function of language instruction but also carries the mission of promoting intercultural exchange and people-to-people connectivity.

With the steady increase in the number of international students studying in China, learning demands have become increasingly diverse. Particularly at the beginner level of Chinese language learning, learners often encounter significant differences and structural difficulties in areas such as pronunciation, vocabulary, Chinese characters, and sentence order. However, the traditional one-size-fits-all classroom model has certain limitations in addressing individual differences. The development of big data, artificial intelligence, and adaptive learning systems has created new technological possibilities for optimizing learning pathways and providing dynamic feedback. Nevertheless, the introduction of technology does not automatically lead to improvements in teaching quality. How to reasonably integrate digital intelligence technologies while respecting the regularity of language acquisition has therefore become an

urgent issue requiring further exploration.

Local universities in Yunnan Province have long recruited international students from Southeast Asia and countries participating in the Belt and Road Initiative. Their student composition closely aligns with regional cooperation patterns, giving them considerable regional representativeness and practical research value. Against this background, the present study focuses on beginner-level Chinese language classrooms in local universities in Yunnan. Through empirical investigation, it analyzes the current application status and practical challenges of digital intelligence technologies, and further explores their mechanisms and optimization pathways in supporting personalized learning. It is hoped that this study will provide both theoretical references and practical implications for the digital intelligence-driven development of International Chinese Education.

2. Literature Review

2.1 Theoretical Foundations

Discussions on the digital-intelligence transformation of International Chinese Education cannot be confined to the efficiency advantages of technological tools (Li et al., 2026). Such a limited perspective makes it difficult to grasp the deeper mechanisms and structural constraints of technology-enhanced learning (Pimmer, 2016). A systematic examination of learning behaviors in digital-intelligence environments requires a multidimensional theoretical framework (Stiakakis & Barboutidis, 2022). This study integrates Structuration Theory, Learning Strategy Theory and Metacognitive Theory, Cognitive Processing Depth Theory, and Situated Learning Theory to construct a

three-level analytical framework—macro, meso, and micro levels (Dimitrieska, 2024). This framework addresses how digital-intelligence technologies are embedded in instructional structures, how learners regulate their learning within technological environments, and how language processing evolves from surface input to deep integration and contextual transfer (Fang & Guo, 2025).

At the macro level, Anthony Giddens' Structuration Theory provides a foundational perspective for understanding how technology is embedded within institutional frameworks (Thompson, 2012). Giddens argues that social structures are not external constraints imposed upon actors, but rather rules and resources that are continuously produced and reproduced through everyday practices (Van Rooyen, 2013). In second language teaching contexts, structural elements such as curriculum progression, instructional norms, and assessment systems constitute the institutional framework of learner action (Duschl et al., 2011). However, Structuration Theory emphasizes that within structural constraints, actors still possess agency to adjust their behaviors through strategic choices (Sarason et al., 2006).

Existing studies have attempted to apply Structuration Theory to educational technology. It has been proposed as a suitable analytical tool for understanding human–technology interaction, and as a meta-framework for designing coherent blended learning experiences (Brownell & Kloser, 2015). It has also been used in research on educational policy implementation and teacher professional development to explain the tension between institutional structures and individual agency (Toom et al., 2015). In the context of digital-intelligence-enabled personalized learning, Structuration Theory suggests

that technology does not operate in a structural vacuum; rather, it is embedded within existing educational systems. Through data tracking and real-time feedback mechanisms, technology enables learners to adjust their learning pathways within institutional boundaries, thereby increasing their behavioral flexibility within structured systems. This provides a macro-level theoretical lens for understanding the regulatory role of digital-intelligence technologies in learning structures.

At the meso level, Learning Strategy Theory serves as the core framework for analyzing the relationship between learners' technological behaviors and learning outcomes. Learning strategies refer to intentional, goal-directed, and observable cognitive and behavioral actions employed by learners to facilitate second or foreign language acquisition (Sommerville et al., 2012). Oxford's taxonomy classifies learning strategies into six categories: metacognitive, affective, social, cognitive, memory-related, and compensation strategies. In the context of autonomous language learning supported by digital-intelligence platforms, this study focuses particularly on cognitive, metacognitive, and affective strategies.

Metacognitive strategies involve planning, monitoring, and evaluating learning processes, serving as a regulatory system that ensures continuous learning progression. These strategies enable learners to set goals, select appropriate approaches, assess their own comprehension, and make timely adjustments when difficulties arise, thereby functioning as a higher-order steering mechanism that oversees the entire learning trajectory. Affective strategies relate to learners' attitudes, self-efficacy, and motivation regulation, which determine the stability and sustainability of learning

engagement. In technology-enhanced environments, where distractions are abundant and self-discipline is constantly tested, affective strategies become particularly critical in sustaining long-term commitment and preventing learning fatigue or avoidance behaviors. Cognitive strategies refer to the direct manipulation of language materials, including encoding, retention, and retrieval processes. These strategies involve specific techniques such as repetition, elaboration, inferencing, and note-taking, all of which facilitate the deep processing and storage of incoming information. From the perspective of learning strategy theory, effective learning depends on the coordinated functioning of these three strategy types. Any imbalance among them—whether an overemphasis on mechanical cognitive drills at the expense of metacognitive reflection, or a neglect of affective regulation—may lead to structural inefficiencies in technology-enhanced learning, ultimately undermining both learner autonomy and overall achievement.

This framework provides an essential analytical tool for diagnosing issues such as an overemphasis on basic practice, insufficient metacognitive support, and weak perceptions of personalized learning support in digital-intelligence environments. Furthermore, Metacognitive Theory enriches the meso-level analysis by defining metacognition as an individual's awareness of their own cognitive processes, cognitive outcomes, and related activities, consisting of metacognitive knowledge, experiences, and monitoring. Metacognitive strategies, including planning, monitoring, and evaluation, play a crucial role in autonomous learning and language acquisition. Research in language learning demonstrates that metacognitive monitoring significantly

influences learners' strategy selection and knowledge construction through self-regulation mechanisms (Lee et al., 2010). This study uses metacognitive monitoring as an interpretive lens to explain structural issues such as fragmented platform usage and insufficiently systematized learning pathways in digital-intelligence environments.

At the micro level, Cognitive Processing Depth Theory and Situated Learning Theory provide theoretical foundations for explaining the depth of language processing and the extension of learning contexts. In language learning contexts, this theory distinguishes between shallow processing (e.g., repetition and pronunciation practice) and deep processing (e.g., semantic integration and contextual transfer) (Shen, 2004). The greater the depth of processing, the stronger and more stable the memory retention.

In International Chinese teaching contexts, this theory provides an operational lens for examining whether learning activities remain at the level of vocabulary repetition and pronunciation imitation or extend to semantic integration and contextual application. It also helps explain the structural imbalance observed in current digital-intelligence learning environments, where basic skill training is well supported, but mechanisms for promoting deep semantic processing and cross-contextual transfer remain underdeveloped.

Meanwhile, Situated Learning Theory, proposed by Arnseth, emphasizes that learning is inherently embedded within activity systems, environments, and cultural contexts (Arnseth, 2008). In language learning, knowledge must be repeatedly activated, transferred, and applied across multiple real-life contexts after being abstracted

from specific learning situations in order to achieve meaningful competence development. This theory provides a strong foundation for analyzing the extension of learning support beyond classrooms, highlighting that the value of digital-intelligence technologies lies not only in extending learning time, but also in constructing multi-contextual learning networks across dormitories, libraries, and daily life environments, enabling high-frequency and low-burden language exposure.

In summary, this study integrates Structuration Theory, Learning Strategy Theory, Metacognitive Theory, Cognitive Processing Depth Theory, and Situated Learning Theory to construct a three-level analytical framework of “macro-level structural embedding, meso-level strategy coordination, and micro-level processing and contextual extension.” This framework provides a systematic theoretical foundation for empirically examining the application status, structural characteristics, and optimization pathways of digital-intelligence technologies in beginner-level personalized Chinese language learning.

2.2 Conceptual Definitions

“Digital-intelligence” refers to an integrative concept combining digitalization and intelligence, whose connotation has been continuously enriched with the development of big data, artificial intelligence, and adaptive learning systems. Digitalization emphasizes the transformation of information from analog to digital form, providing a technical foundation for data recording, storage, and transmission. Intelligence, built upon digitalization, introduces algorithmic analysis and automated decision-making capabilities, enabling systems to perform differentiated recognition, recommendation, and regulation based on data characteristics. In the field of

education, digital-intelligence technologies are reflected in the continuous collection of learning behavior data, the dynamic adaptation of learning pathways, and the real-time generation of instructional feedback.

In this study, “digital-intelligence” specifically refers to a set of technologies represented by Chinese learning applications, AI tools, online video platforms, and school-based online learning systems in beginner-level Chinese learning contexts. These tools integrate functions such as vocabulary memorization, listening practice, oral proficiency assessment, and contextual input, providing learners with an extracurricular autonomous learning environment while also serving as technological mediators for differentiated interaction between teachers and learners.

Personalized learning refers to a pedagogical concept and practice model that adjusts learning objectives, content, pathways, and assessment methods flexibly according to individual learner differences—including language foundation, cognitive style, learning pace, and interest preferences. Compared with the traditional uniform-paced and standardized classroom teaching model, personalized learning places greater emphasis on the learner’s agency as the subject of learning and advocates providing responsive space for individual differences within institutional frameworks.

In digital-intelligence environments, the realization of personalized learning typically relies on three mechanisms: (1) identifying learners’ competence structures and weaknesses through learning data tracking; (2) recommending adaptive learning resources and tasks based on analytical results; and (3) providing visualized learning trajectories and tools for

self-regulation. In this study, “personalized learning” focuses on the digital-intelligence learning context of beginner-level international students in local universities in Yunnan Province, emphasizing that within a unified curricular structure, data-driven differentiation and resource matching can provide learners with more targeted learning support and strategic adjustment space.

“Beginner-level Chinese learning” in this study refers to the initial stage of Chinese as a second language learning among international students in China. At this stage, learners typically master a limited number of basic vocabulary items and simple sentence patterns. Their phonological system is not yet stable, their abilities in Chinese character recognition and writing are still in the early stages, and their cross-cultural pragmatic awareness remains limited.

At the linguistic skill level, core tasks for beginner learners include tone discrimination and pronunciation imitation, basic vocabulary accumulation, acquisition of fundamental syntactic structures, and oral expression in simple communicative contexts. Existing studies show that learners at this stage commonly face structural difficulties such as negative transfer from their native phonological systems to Chinese tones, difficulties in mapping between Chinese characters and pronunciation, and cross-linguistic interference in syntactic order.

Among international students in local universities in Yunnan Province, the learner population is mainly composed of students from Southeast Asia and Belt and Road Initiative countries. Differences in native language backgrounds—such as Thai, Lao, and Burmese—lead to particularly pronounced phonological and syntactic

variations. Therefore, “beginner-level Chinese learning” in this study is not only a descriptor of language proficiency level, but also a set of teaching contexts characterized by specific cognitive load and learning difficulties.

The significance of digital-intelligence technologies at this stage lies in their ability to provide high-frequency input, immediate feedback, and adaptive learning pathways, thereby helping learners gradually establish stable language processing structures and autonomous learning capabilities while overcoming initial learning barriers.

3. Research Methodology

3.1 Research Design

This study adopts a quantitative research-oriented survey design, aiming to systematically examine the application status, structural characteristics, and practical challenges of digital-intelligence technologies in personalized learning for beginner-level international Chinese learners. The research design is based on the previously constructed three-level analytical framework of “macro-level structural embedding, meso-level strategy coordination, and micro-level processing and contextual extension.” It focuses on three core dimensions: learners’ usage behaviors of digital-intelligence tools (including tool types and usage purposes), learners’ perceived attitudes toward technology usefulness, ease of use, and personalized support, as well as the structural characteristics of support reflected in cognitive, metacognitive, and affective learning strategies.

Data were collected through a questionnaire survey, and descriptive statistical analysis and structural analysis methods were employed to identify structural issues in the current

digital-intelligence learning environment, including an overemphasis on basic skill development, fragmented platform usage, and insufficient perception of personalized learning support. These findings provide empirical evidence for subsequent optimization proposals.

In terms of research logic, this study follows an applied research model of “status diagnosis–structural analysis–optimization suggestions.” First, the current situation is systematically described through the distribution of digital-intelligence tool usage and learners’ perceptual levels based on questionnaire data. Second, drawing on Learning Strategy Theory, the study analyzes the balance and deficiencies of technological support from three dimensions: cognitive, metacognitive, and affective strategies. Finally, based on empirical findings, three transformation pathways are proposed: shifting from basic-skill concentration to comprehensive competence integration, from parallel tool usage to systematic pathway integration, and from functional feedback to self-regulatory mechanism development. The overall research logic follows a chain of “theoretical guidance–data support–problem diagnosis–solution generation,” ensuring that the conclusions are both empirically grounded and responsive to the practical needs of digital-intelligence transformation in International Chinese Education.

In terms of research participants and context, this study focuses on beginner-level international students studying at local universities in Yunnan Province. This population was selected for several reasons. First, local universities in Yunnan have long enrolled international students from Southeast Asia and Belt and Road Initiative countries, resulting in a regionally representative student

composition. Second, beginner-level Chinese learners commonly face difficulties in pronunciation, vocabulary acquisition, Chinese character learning, and syntactic organization, with significant individual differences and a strong demand for personalized learning support. Third, this group frequently uses digital-intelligence tools such as Chinese learning apps, AI-based tools, and video platforms in daily learning, providing a suitable basis for investigating the current status of technology use. Data collection was conducted in 2026, using a combination of convenience sampling and snowball sampling. Questionnaires were distributed through both online and offline channels, and valid responses were collected for subsequent analysis.

In summary, this research design is grounded in Learning Strategy Theory and Structuration Theory at the theoretical level, employs questionnaire survey as the core empirical tool, and integrates descriptive statistics with structural comparison methods in analysis. It systematically addresses a series of interrelated research questions concerning digital-intelligence technologies in beginner-level personalized Chinese learning, including what is being used, how effective it is, what structural problems exist, and how it can be optimized.

3.2 Research Instruments

This study primarily adopts a questionnaire survey method. The questionnaire design is grounded in Learning Strategy Theory and the Technology Acceptance Model, and is informed by relevant studies on the application of digital-intelligence technologies in International Chinese Education. It is further developed in accordance with the actual learning context of beginner-level Chinese international students in local universities in Yunnan Province. The

questionnaire aims to systematically collect multidimensional data on learners' use behaviors of digital-intelligence tools, usage attitudes, and perceptions of personalized learning, thereby providing empirical support for subsequent status diagnosis and structural analysis.

The questionnaire consists of four sections. The first section collects demographic information and learning background, including learners' nationality, native language background, and duration of Chinese language study, in order to describe the basic characteristics of the sample. The second section investigates the use behaviors of digital-intelligence tools, using multiple-choice questions. The specific items include "What do you mainly use these tools for?" (with options covering vocabulary, listening, speaking, Chinese characters, review, and daily communication), and "Which tools do you usually use to learn Chinese?" (with options including Chinese learning apps, dictionaries or memorization tools, video platforms, AI tools, and school-based online learning platforms). The statistical results of these items are presented in Tables 1 and 2 in the second part of the paper, aiming to reveal learners' usage preferences and tool-selection patterns at the level of cognitive strategies.

The third section consists of a digital-intelligence learning perception scale, designed with multiple items measured on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). The scale covers four dimensions: perceived personalized learning, perceived usefulness and ease of use, learning motivation and self-efficacy, and usage attitude and continuance intention. The fourth section includes open-ended questions designed to collect learners' specific difficulties and suggestions regarding the use of

digital-intelligence tools, serving as a qualitative complement to the quantitative data.

Prior to formal distribution, the questionnaire was reviewed for validity by three experts in the field of International Chinese Education, and several items were revised based on their feedback. Subsequently, a pilot test was conducted with 15 international students of similar backgrounds who were not included in the formal sample to examine clarity and completion time. The results indicated that the average completion time was approximately 8–10 minutes, with clear item wording and no significant ambiguity or comprehension difficulties.

Regarding reliability and validity, internal consistency analysis was conducted on the valid samples collected from the formal survey. The results showed that the Cronbach's alpha coefficient of the overall scale was 0.939, and all sub-dimensions exceeded 0.85, indicating high reliability. In terms of validity, exploratory factor analysis was conducted on the scale items. The KMO value was 0.761, and Bartlett's test of sphericity was statistically significant ($p < 0.001$), indicating that the data were suitable for factor analysis and that the scale demonstrated good construct validity, effectively reflecting the predefined perceptual dimensions of this study.

3.3 Sampling and Data Collection

The participants in this study were beginner-level international students of Chinese enrolled in local universities in Yunnan Province. The selection of this group is based on the following considerations. First, local universities in Yunnan have long recruited international students from Southeast Asia and countries along the Belt and Road Initiative, resulting in a regionally representative student population. In addition, learners from different native

language backgrounds show significant differences in phonology and syntax, which leads to a higher demand for personalized learning support. Second, beginner-level Chinese learners commonly and frequently use digital-intelligence tools in their daily learning, making them an appropriate population for investigating the current status of technology application. The survey was conducted from March to April 2026.

A combination of convenience sampling and snowball sampling was employed. First, the researchers contacted instructors of beginner-level Chinese classes through the International Education Colleges of the affiliated universities. With their consent, paper questionnaires were distributed in classroom settings. Considering the mobility of international students and the fact that some students were engaged in internships or self-study, electronic questionnaires were also distributed via social media platforms such as WeChat and Messenger to students who had already established contact with the researchers. Respondents were further encouraged to share the questionnaire link with peers who met the inclusion criteria in order to expand the sample coverage.

The inclusion criteria were as follows: (1) non-Chinese native speakers; (2) currently at beginner or elementary level in Chinese proficiency (based on placement test results or self-assessment); (3) having used at least one type of digital-intelligence tool (including but not limited to Chinese learning apps, AI tools, and video platforms) to support Chinese learning within the past three months; and (4) voluntary participation with the ability to independently complete the questionnaire.

The data collection procedure was conducted as follows. For the offline

channel, this study collected questionnaires from international students at three universities in Yunnan Province, China. Paper questionnaires were distributed after beginner-level Chinese classes, and the researchers explained the purpose of the survey and instructions for completion, emphasizing anonymity and confidentiality. Completed questionnaires were collected on site. For the online channel, the researchers designed an electronic questionnaire using the Wenjuanxing platform, generating a QR code and link, which were distributed through international student WeChat groups and the researchers' personal social networks. Mandatory questions and logical skip settings were used to ensure data completeness. Data collection lasted four weeks, during which two reminders were issued to improve the response rate.

A total of 52 questionnaires were collected. After item-by-item screening, 8 invalid responses were excluded, resulting in 44 valid questionnaires, with an effective response rate of 84.6%. The criteria for invalid responses included completion time of less than 3 minutes, uniform selection of the same option for all Likert-scale items, irrelevant responses in open-ended questions, or obviously careless answers. Among the valid samples, learners' native languages included Thai, Lao, Burmese, and Vietnamese. The distribution of Chinese learning duration was as follows: 11.4% had studied Chinese for less than 6 months, 6.8% for 6–12 months, and 81.8% for more than 12 months (consistent with the statement in Section 2 that “81.8% of students have studied Chinese for more than 12 months”). The sample structure adequately reflects the basic characteristics of beginner-level international Chinese learners in local universities in Yunnan Province, providing a reliable foundation for

subsequent data analysis.

3.4 Data Analysis

This study employs quantitative analysis methods to process and analyze the collected valid questionnaire data using SPSS 26.0. The data analysis procedure consists of the following steps:

First, descriptive statistical analysis is conducted on the demographic characteristics and learning background of the sample, including variables such as learners' native language background and duration of Chinese learning. Frequency and percentage distributions are calculated to present the basic structural characteristics of the sample.

Second, frequency analysis is applied to the items related to

digital-intelligence tool usage behavior. Specifically, for the item "What do you mainly use these tools for?", the frequencies and percentages of each option (vocabulary, listening, speaking, Chinese characters, review, and daily communication) are calculated to reveal learners' usage preferences at the level of cognitive strategies. For the item "Which tools do you usually use to learn Chinese?", the frequencies and percentages of different tools (Chinese learning apps, dictionaries or memorization tools, video platforms, AI tools, and school-based online learning platforms) are analyzed to present the structure of learners' tool selection. The results of these analyses are presented in Tables 1 and 2 of the paper.

Table 1. Distribution of Usage Purposes of Digital-Intelligence Tools in Beginner-Level Chinese Learning

Item	Options	Frequency	Percentage
What do you mainly use these tools for?	Vocabulary	40	90.9
	Listening	29	65.9
	Speaking	25	56.8
	Chinese Characters	25	56.8
	Review	17	38.6
	Daily Communication	19	43.2

(Source: Peng Xueyuan)

Table 2. Distribution of Types of Digital-Intelligence Tools Used in Beginner-Level Chinese Learning

Item	Options	Frequency	Percentage
Which tools do you usually use to learn Chinese?	Chinese learning apps	32	72.7
	Dictionaries or memorization tools	20	45.5
	Video platforms	28	63.6
	AI tools	23	52.3
	School-based online learning platforms	8	18.2
	Others	2	4.5

(Source: Peng Xueyuan)

Next, descriptive statistical analysis and reliability and validity testing were conducted on the digital-intelligence

learning perception scale data. For the descriptive statistics, the mean, standard deviation, minimum, and maximum

values of each dimension (perceived personalized learning, perceived usefulness and ease of use, learning motivation and self-efficacy, and usage attitude and continuance intention) were

calculated in order to compare the level differences among different perceptual dimensions. The results are presented in Table 3.

Table 3. Descriptive Statistics of Scores for Each Dimension

Dimension		Minimum	Maximum	Mean	Standard Deviation
Perceived Personalized Learning		2.17	5	3.73	0.67
Perceived Usefulness & Ease of Use		2.33	5	3.94	0.71
Learning Motivation & Self-Efficacy		2	5	3.88	0.76
Usage Attitude & Continuance Intention		2.25	5	3.97	0.76

(Source: Peng Xueyuan)

In terms of reliability testing, Cronbach's alpha coefficient was used to assess the internal consistency of the scale. For validity testing, the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity in exploratory factor analysis were employed to evaluate the construct validity of the scale. The results show that the Cronbach's alpha coefficient of the overall scale is 0.939, the KMO value is 0.761, and Bartlett's test of sphericity reaches a statistically significant level ($p < 0.001$), indicating good reliability and suitability for factor structure analysis.

Finally, based on the results of descriptive statistics, this study conducts an interpretative analysis of the structural characteristics reflected in the data within the framework of Learning Strategy Theory. The analysis focuses on comparing differences among various dimensions, including usage purposes (vocabulary and listening vs. review and daily communication), types of tools (open platforms vs. school-based platforms), and perceptual dimensions (perceived personalized learning vs. usage attitude). Through this comparison,

structural issues in the current digital-intelligence learning environment are identified, such as an overemphasis on cognitive strategy support for basic skill practice, insufficient metacognitive strategy support, and weak coordination between affective and metacognitive strategies. All statistical analyses are conducted at a significance level of 0.05. The data analysis process ensures objectivity and transparency, providing an empirical basis for subsequent optimization proposals.

4. Results

4.1 Descriptive Characteristics of the Sample

A total of 44 valid questionnaires were collected in this study, with an effective response rate of 84.6%. The sample consisted of beginner-level Chinese learners enrolled in three local universities in Yunnan Province. The participants were primarily from Thailand, Laos, Myanmar, Vietnam, and other Southeast Asian countries along the Belt and Road Initiative. In terms of native language background, Thai speakers accounted for the largest proportion, followed by Lao, Burmese,

and Vietnamese speakers, with a small number of learners whose native languages were Khmer or Malay. This distribution is highly consistent with the regional cooperation pattern of Yunnan's local universities, which have long recruited international students from Southeast Asia, indicating good regional representativeness of the sample.

Regarding the duration of Chinese learning, among the 44 respondents, 5 students (11.4%) had studied Chinese for less than 6 months; 3 students (6.8%) had studied for 6 to 12 months; and 36 students (81.8%) had studied for more than 12 months. These results indicate that the majority of respondents have accumulated a certain level of Chinese learning experience and are not absolute beginners, although they are still within the beginner proficiency range. This learning-duration structure helps to interpret subsequent digital-intelligence tool usage behaviors and perceptual attitudes, as learners with longer learning experience tend to have richer exposure to and evaluation of tool functionality and support effectiveness.

In terms of gender and age distribution, there were 18 male respondents (40.9%) and 26 female respondents (59.1%). The age range was mainly concentrated between 18 and 25 years old, accounting for 86.4% of the total sample, while the remaining participants were aged 26 to 30. Overall, the sample shows a youthful profile, which is consistent with the typical age group of international students pursuing undergraduate or language training programs in China. All respondents reported having used at least one type of digital-intelligence tool for Chinese learning within the past three months, meeting the inclusion criteria of this study. In summary, the sample demonstrates a reasonable distribution in terms of native language background,

learning duration, age, and gender, providing a reliable data foundation for subsequent structural analysis of digital-intelligence tool usage behavior and learning perceptions.

4.2 Descriptive Statistical Results of Digital-Intelligence Tool Usage Behavior

This study conducted frequency analysis on learners' usage purposes and types of digital-intelligence tools. In terms of usage purposes, the results show significant differences in learners' engagement across different language skill areas. Specifically, vocabulary learning recorded the highest usage frequency, with 40 out of 44 respondents selecting this option, accounting for 90.9%. Listening practice ranked second, with 29 users (65.9%). Both speaking practice and Chinese character learning were selected by 25 respondents each, accounting for 56.8% respectively. Daily communication was used by 19 respondents (43.2%), while review and consolidation recorded the lowest usage, with 17 respondents (38.6%). These findings indicate that vocabulary enhancement and listening practice are the primary application scenarios of digital-intelligence tools, whereas integrative activities such as review and daily communication are used less frequently.

In terms of tool types, learners tend to adopt a diversified range of digital-intelligence platforms. Chinese learning apps are the most commonly used tools, with 32 out of 44 respondents (72.7%). Video platforms follow closely, used by 28 respondents (63.6%). AI tools are used by 23 respondents (52.3%), while dictionaries or memorization tools are used by 20 respondents (45.5%). School-based online learning platforms show the lowest usage rate, with only 8 respondents (18.2%). In addition, 2 respondents reported using other types

of tools (4.5%). The distribution indicates that open-access, multifunctional third-party platforms (such as apps, video platforms, and AI tools) enjoy relatively high usage rates, whereas school-provided platforms that are directly linked to the curriculum are used significantly less frequently.

Taken together, these results reveal two fundamental characteristics of learners' digital-intelligence tool usage behavior. First, usage purposes are highly concentrated on basic skill training, particularly vocabulary and listening, while engagement in higher-level integrative activities such as review and daily communication remains limited. Second, tool selection is primarily driven by independently downloaded open platforms, whereas school-based online learning systems play a relatively weak guiding role in the overall learning structure. These patterns provide a behavioral foundation for subsequent analysis of the structural characteristics of digital-intelligence technology support.

4.3 Descriptive Statistical Results of Each Dimension of Digital-Intelligence Learning Perception

This study calculated the minimum, maximum, mean, and standard deviation for the four dimensions included in the scale: perceived personalized learning, perceived usefulness and ease of use, learning motivation and self-efficacy, and attitude toward use and continuance intention.

In terms of mean distribution, the dimension of attitude toward use and continuance intention obtained the highest score ($M = 3.97$, $SD = 0.76$), indicating that most learners hold a positive attitude toward digital-intelligence tools and are willing to continue using them in the future. The dimension of perceived usefulness and ease of use ranked second ($M = 3.94$,

$SD = 0.71$), suggesting that learners generally recognize the practical value and operational convenience of digital-intelligence tools in Chinese language learning. The mean score of learning motivation and self-efficacy was 3.88 ($SD = 0.76$), which is at a moderately high level, reflecting that digital-intelligence environments can, to some extent, enhance learners' confidence and engagement. In contrast, perceived personalized learning recorded the lowest mean score ($M = 3.73$, $SD = 0.67$) among the four dimensions, indicating a relatively weaker perception.

In terms of dispersion, the standard deviations of all dimensions ranged from 0.67 to 0.76, indicating some individual differences in learners' evaluations, while the overall distribution remained relatively concentrated. Among them, perceived personalized learning showed the smallest standard deviation ($SD = 0.67$), suggesting a relatively high level of agreement among learners. They generally believed that current digital-intelligence tools still have room for improvement in providing differentiated support based on individual proficiency levels and learning progress.

Overall, these results reveal a structural imbalance: learners demonstrate relatively high evaluations of the usefulness, ease of use, and behavioral intention associated with the tools, whereas their perception of personalization remains comparatively weaker. This finding suggests that while current digital-intelligence technologies are positively recognized at the affective and operational levels, limitations remain in accurately addressing individual differences and optimizing adaptive learning pathways, providing a key entry point for subsequent optimization strategies.

4.4 Results of Reliability and

Validity Testing

To ensure the reliability and validity of the questionnaire data, this study conducted reliability and validity tests on the 44 valid responses collected from the formal survey. Reliability was assessed using Cronbach's alpha coefficient to examine the internal consistency of the scale. The results show that the Cronbach's alpha coefficient for the overall scale is 0.939, indicating a very high level of reliability. The Cronbach's alpha coefficients for each sub-dimension are as follows: perceived personalized learning (0.87), perceived usefulness and ease of use (0.89), learning motivation and self-efficacy (0.88), and attitude toward use and continuance intention (0.86). All values exceed the acceptable threshold of 0.85, demonstrating strong internal consistency among items and stable measurement reliability.

Validity was examined through the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity in exploratory factor analysis to assess construct validity. The KMO value was 0.761, which falls between 0.7 and 0.8, indicating a relatively strong shared variance among variables and suitability for factor analysis. Bartlett's test of sphericity yielded an approximate chi-square value of 428.63 with degrees of freedom $df = 78$, and a significance level of $p < 0.001$. The result is statistically significant, rejecting the null hypothesis that the correlation matrix is an identity matrix, thereby confirming that the data are appropriate for factor analysis.

Overall, these indicators demonstrate good construct validity of the scale, which effectively reflects the four predefined perceptual dimensions of this study and provides methodological support for subsequent comparative analyses across dimensions.

4.5 Summary of Results

Based on the above descriptive statistical results and reliability and validity tests, the findings of this section can be summarized into the following four points:

First, regarding sample characteristics, the 44 valid respondents mainly came from Southeast Asian countries such as Thailand, Laos, Myanmar, and Vietnam. A total of 81.8% of them had more than 12 months of Chinese learning experience, indicating a certain level of prior learning foundation. In addition, all respondents reported having used digital-intelligence tools to assist their Chinese learning within the past three months.

Second, in terms of digital-intelligence tool usage behavior, learners' usage purposes were highly concentrated on vocabulary learning (90.9%) and listening practice (65.9%), while relatively lower usage rates were observed for integrative activities such as review (38.6%) and daily communication (43.2%). Regarding tool types, Chinese learning apps (72.7%), video platforms (63.6%), and AI tools (52.3%) were the most frequently used, whereas school-based online learning platforms had a notably low usage rate of only 18.2%.

Third, the scores across different dimensions of digital-intelligence learning perception showed an unbalanced pattern. The dimensions of attitude toward use and continuance intention ($M = 3.97$), perceived usefulness and ease of use ($M = 3.94$), and learning motivation and self-efficacy ($M = 3.88$) were all at a moderately high level, while perceived personalized learning recorded the lowest score ($M = 3.73$), indicating that learners' perception of personalized support from digital tools remains relatively weak.

Fourth, the results of reliability and

validity testing showed that the overall Cronbach's alpha coefficient was 0.939, the KMO value was 0.761, and Bartlett's test of sphericity was statistically significant ($p < 0.001$). These results indicate that the questionnaire data have high reliability and good construct validity, providing a solid empirical foundation for subsequent discussion and optimization analysis.

5. Discussion and Conclusions

5.1 Discussion of Findings

Based on the questionnaire survey of 44 junior Chinese language learners at universities in Yunnan Province, this study systematically examined the current application status and structural characteristics of digital-intelligence technologies in personalized learning. The empirical results reveal three key findings, corresponding to the previously identified structural issues of "cognitive strategy support biased toward basic practice," "weak metacognitive strategy support," and "insufficient coordination between affective and metacognitive dimensions," further confirming the explanatory power of the theoretical framework.

First, at the level of cognitive strategies, learners' use of digital-intelligence tools is highly concentrated on basic skill training such as vocabulary and listening (90.9% and 65.9%, respectively), while the usage rates for integrative activities such as review and daily communication are both below 45%. This finding is consistent with the predictions of the levels-of-processing theory : technological environments are more effective in supporting shallow processing tasks such as repetition and imitation, as these tasks provide immediate feedback and quantifiable outcomes, thereby generating short-term achievement satisfaction. In contrast,

deeper processing activities such as meaning integration and contextual transfer require more complex task design and higher cognitive engagement, yet current digital-intelligence platforms provide insufficient guidance for such advanced activities. As a result, the learning structure demonstrates a pattern of "localized enhancement but overall imbalance," where vocabulary size and listening accuracy may improve, but communicative competence and pragmatic awareness develop more slowly.

Second, at the metacognitive strategy level, learners tend to use open-access platforms such as mobile applications (72.7%), video platforms (63.6%), and AI tools (52.3%), while the usage rate of school-based online learning platforms is only 18.2%. Considering that 81.8% of the sample have more than 12 months of learning experience, this "parallel tool use and fragmented pathways" pattern reflects a lack of overall planning and monitoring mechanisms in learners' learning processes. Metacognitive theory emphasizes that effective learning requires regulatory processes such as goal setting, progress monitoring, and strategy adjustment. However, learners in this study frequently switch between platforms based on immediate needs, without forming a structured, hierarchical learning trajectory centered on clear learning objectives. The lack of integration among platform data and the fragmentation of learning records further prevent learners from developing a systematic understanding of the long-term development of their competence structure.

Third, at the level of affective-metacognitive coordination, the dimensions of attitude toward use and continuance intention (3.97), perceived usefulness and ease of use (3.94), and learning motivation and

self-efficacy (3.88) are all at a moderately high level, whereas perceived personalized learning records the lowest score (3.73). This gap indicates that although learners recognize the usefulness of digital tools and maintain positive attitudes toward them, they have not yet fully experienced the system's capacity to dynamically respond to individual differences. From the perspective of strategy interaction, affective strategies sustain learning motivation, but insufficient metacognitive regulation and feedback mechanisms limit the effectiveness of pathway adjustment and developmental guidance. As a result, personalized support remains at a functional level rather than being translated into a meaningful developmental experience. Learners are positioned as "data-recorded subjects" rather than "understood learners," and learning analytics have not yet been effectively transformed into tools for self-regulated learning.

5.2 Theoretical Contributions and Practical Implications

The theoretical contributions of this study are mainly reflected in three aspects. First, it constructs a three-level analytical framework of "macro (structure–agency) – meso (learning strategy coordination) – micro (levels of processing and contextual extension)", integrating structuration theory and learning strategy theory into research on digital-intelligence in international Chinese education. This moves beyond previous studies that focused solely on technological functions or user attitudes, and provides a systematic theoretical tool for understanding how technology is embedded within language learning structures. Second, the study empirically reveals an imbalance in the support of cognitive, metacognitive, and affective strategies in digital-intelligence environments, thereby enriching the

application of learning strategy theory in technology-mediated learning contexts. Third, through the measurement and analysis of the dimension of perceived personalized learning, the study distinguishes between "tool recognition" and "personalized experience," and demonstrates that a high attitude score does not necessarily indicate strong personalized support, thus providing a clear target for future optimization interventions.

In terms of practical implications, the findings of this study offer three guiding directions for the design and improvement of digital-intelligence-based beginner Chinese learning. First, instructional content design should shift from single-skill training to integrated competence development by constructing task chains that connect vocabulary acquisition, listening comprehension, speaking production, and writing output, thereby avoiding fragmented learning activities. Second, tool usage should move from parallel multi-platform use to a systematically integrated learning pathway, establishing a "main platform–auxiliary platform" structure in which a school-based platform or a core application serves as the central trajectory for competence accumulation, while other tools are used only for contextual expansion and targeted reinforcement. At the same time, a functional linkage mechanism across pre-class, in-class, and post-class stages should be established. Finally, feedback mechanisms should be upgraded from functional feedback to self-regulated learning support by incorporating visualized learning curves, error-type clustering analysis, and staged mastery indicators. These designs can help learners identify weaknesses in their competence structure and adjust their learning plans accordingly, thereby

enabling learning data to genuinely inform the decision-making process.

5.3 Research Limitations and Future Directions

This study has several limitations. First, the sample size is relatively small (N = 44) and is limited to universities in Yunnan Province. Therefore, the generalizability of the findings to other regions or learners from different national backgrounds remains to be further examined. Second, this study adopts a cross-sectional survey design, which only captures learners' behaviors and perceptions at a single point in time and cannot track the long-term developmental trajectory of learners' abilities under digital-intelligence support. Third, the study focuses on learners' self-reported usage behaviors and perceptions without directly measuring their actual language proficiency gains; thus, the causal relationship between "perceived personalized learning experience" and actual learning outcomes still requires further empirical validation. Fourth, key terms in the questionnaire such as "Chinese learning apps" and "AI tools" are relatively broad and do not distinguish between specific tool functionalities (e.g., vocabulary flashcard-based apps versus conversational AI chatbots), which may obscure the differentiated effects of various tools on learning strategy support.

Future research may develop in the following directions. First, the sample scope and diversity should be expanded to include learners from different regions and different proficiency levels for comparative analysis. Second, longitudinal research designs should be adopted, combining learning logs and platform tracking data to analyze learners' strategy evolution and competence development over time in digital-intelligence environments. Third,

experimental or quasi-experimental designs could be introduced to examine the effects of different interventions (e.g., learning path guidance prompts or metacognitive strategy training) on personalized learning perception and actual learning outcomes. Fourth, mixed-method approaches should be employed, incorporating in-depth interviews or focus groups to explore learners' specific interpretations and experiential differences regarding "personalized support," thereby providing more nuanced user insights for platform optimization.

5.4 Conclusion

In summary, this study focused on junior Chinese language learners at universities in Yunnan Province. Based on a three-level analytical framework integrating structuration theory, learning strategy theory, and levels-of-processing theory, the study used a questionnaire survey to reveal the practical challenges of digital-intelligence technologies in supporting personalized learning. The findings indicate that cognitive strategy support is biased toward basic practice, weak metacognitive support leads to fragmented learning pathways, and insufficient coordination between affective and metacognitive dimensions results in lower perceived personalization than tool acceptance.

The study further proposes a threefold optimization pathway: shifting from basic skill accumulation to integrated competence development, from parallel tool usage to systematic learning pathway integration, and from functional feedback to self-regulated learning mechanisms. The results suggest that while digital-intelligence technologies have established a solid foundation in beginner-level Chinese learning, achieving genuine improvement in personalization requires moving beyond mere "tool usage" toward deeper integration at the levels of

content structure, learning pathways, and feedback systems.

These findings not only provide actionable directions for improving digital-intelligence practices in

international Chinese education but also expand the application of learning strategy theory in technology-enhanced learning contexts.

Appendix

Table 1. Distribution of Usage Purposes of Digital-Intelligence Tools in Beginner-Level Chinese Learning

Item	Options	Frequency	Percentage
What do you mainly use these tools for?	Vocabulary	40	90.9
	Listening	29	65.9
	Speaking	25	56.8
	Chinese Characters	25	56.8
	Review	17	38.6
	Daily Communication	19	43.2

(Source: Peng Xueyuan)

Table 2. Distribution of Types of Digital-Intelligence Tools Used in Beginner-Level Chinese Learning

Item	Options	Frequency	Percentage
Which tools do you usually use to learn Chinese?	Chinese learning apps	32	72.7
	Dictionaries or memorization tools	20	45.5
	Video platforms	28	63.6
	AI tools	23	52.3
	School-based online learning platforms	8	18.2
	Others	2	4.5

(Source: Peng Xueyuan)

Table 3. Descriptive Statistics of Scores for Each Dimension

Dimension	Minimum	Maximum	Mean	Standard Deviation
Perceived Personalized Learning	2.17	5	3.73	0.67
Perceived Usefulness & Ease of Use	2.33	5	3.94	0.71
Learning Motivation & Self-Efficacy	2	5	3.88	0.76
Usage Attitude & Continuance Intention	2.25	5	3.97	0.76

(Source: Peng Xueyuan)

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