Pak. j. life soc. Sci. (2024), 22(2): 3939-3952 E-ISSN: 2221-7630;P-ISSN: 1727-4915

Pakistan Journal of Life and Social Sciences

www.pjlss.edu.pk

https://doi.org/10.57239/PJLSS-2024-22.2.00291

RESEARCH ARTICLE

Network Autonomous Learning and Student Training Education System under Human-computer Interaction Environment

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ARTICLE INFO

Received: Jun 15, 2024

Accepted: Sep 2, 2024

Keywords

Online self-learning

Cultivating education system

Neural network algorithm

Human-computer interaction

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ABSTRACT

With the popularization of the Internet, more and more information can be inquired through the Internet, which also corresponds to the Chinese proverb, "You can know the world without going out at home." With the development of human-computer interaction systems, online learning has gradually become a mainstream. Self-directed learning is to determine learning goals, determine learning content, determine learning process, select appropriate learning methods, master learning process, and self-evaluate. The study of Japanese includes a large amount of relevant knowledge, including language, literature, history, politics, economy, diplomacy, social culture, etc., and has certain professional skills and skills. Therefore, this paper proposes a research on the network autonomous learning and student training education system in the environment of human-computer interaction. It firstly introduces the human-computer interaction system and its structure. Then based on the neural network algorithm to analyze the network self-learning algorithm, this paper puts forward corresponding suggestions for improvement, and conducts a questionnaire survey on Japanese majors in a university to analyze their self-learning ability. Finally, it analyzes its education system and puts forward some opinions. The results of the experiment showed that 54% of the people believed that they could learn autonomously even when the teacher was away. 22% said no, and 24% said they were not sure. This is enough to show that the school's students are not independent enough, and most students seldom study independently.

INTRODUCTION

With the development of the Internet, the resources of the Internet are increasingly abundant, it has penetrated into people's lives, and it is also changing people's way of life, communication, and learning. With the advent of the Internet era, the traditional Japanese teaching mode has also been affected to a certain extent, and the traditional teaching mode dominated by "teacher teaching" can no longer meet the requirements of the new situation. Various online resources related to Japanese, especially under the guidance of teachers, are of great significance to the autonomous development of Japanese learners.

Since the 1980s, Western scholars have introduced the concept of "learner autonomy" into modern education, and "autonomous learning" has gradually become the focus of the education circle. With the development of computer and information technology, more and more resources are available on the network, mobile terminals are updated faster and faster, and information on the network is more and more convenient. These non-physical, high-value information resources have become important resources for students to learn independently. For Japanese learners born in the 1980s, a piece of Japanese, a Japanese newspaper, and a Japanese recording may all be of great value. But now, Japanese dramas, Japanese learning websites, and Japanese information are all new learning experiences for Japanese learners. However, on the Internet, how to make better use of Japanese-related information resources to promote Japanese learning has become a new research field. Taking Japanese network resources as an example, this article discusses how to use network resources to improve the autonomy of Japanese in the network environment from the perspective of teaching practice.

This paper mainly discusses how to establish an independent network autonomy and student training system under the condition of human-computer interaction. First of all, a questionnaire survey was conducted on Japanese majors, and the teaching system was analyzed, and suggestions for improvement were given. The innovation of this article is that the research value of the article is very high, there are few research literatures in Japanese, and the data collection of this experiment is also very accurate, and there are many questions in the questionnaire, which can better experience the specific situation.

RELATED WORK

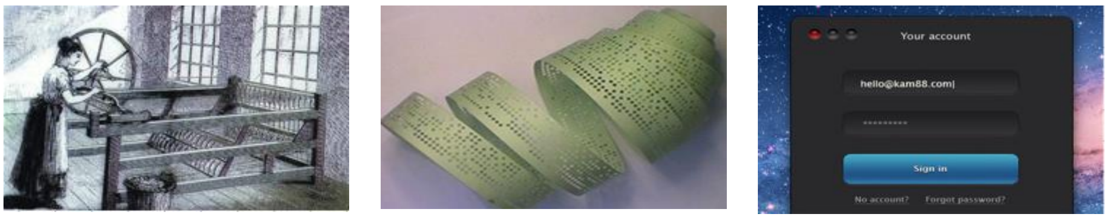
Online course learning is increasingly concerned with the extent to which learners concentrate and self-regulate when they are isolated from classmates and teachers. To address this issue, Zhou, Zhou & Zhu (2021) collected quantitative and qualitative data from a sample of 580 Chinese university learners from different majors who attended online English courses in emergency distance teaching (ERT) mode during COVID-19. As education transitions to online solutions, teachers and students need to adjust their teaching and learning through different forms of monitoring, supervision and assessment. Using a sample of 276 student participants, Rivers, Nakamura & Vallance (2022) reported on a Japanese university that moved all regular face-to-face classes online for a short period of time during 2020. Self-regulated learning is designed to test a major paper that online self-regulated learning affects performance. Autonomy and self-study are ongoing challenges for universities in general, and language centers in particular for language learning and acquisition. The Universities of Modena and Reggio Emilia have always focused on fostering student autonomy and developing customized language learning activities. In all the activities handled by the language center, Marazzi (2019) conducted self-directed learning through the establishment of appropriate laboratories, as well as through the use of Moodle to reach some traditional teaching support measures for students who are absent. Santubera, et al., (2020) presented the validation results of the Online Self-Regulated Learning Questionnaire (OSLQ). The adaptation was based on a method retranslated from the original version of the document and a subsequent completed pilot test with a multidisciplinary sample of 238 college students. They only study autonomous learning, but do not optimize it, so this paper proposes to use neural network algorithm to optimize it.

Neural network is usually optimized by a learning method based on mathematical statistics type, so artificial neural network is also a practical application of mathematical statistics method. The aim of Jae-Hong L was to develop a computer-aided detection system based on a deep convolutional neural network (CNN) algorithm and to evaluate the potential usefulness and accuracy of the system for the diagnosis and prediction of periodontal compromised teeth (PCT) (Lee, et al., 2018). Specifically, the task of noticing and separating two competing sounds is particularly difficult, unlike normal hearing listeners, as shown in a small sub-experiment. In the main experiment, the competitive speech advantage of Bramslw L's deep neural network (DNN)-based stream separation enhancement algorithm was tested on hearing-impaired listeners (Bramsløw, et al., 2018). The machining accuracy will be attenuated due to thermal factors. Using the powerful self-learning and data fitting capabilities of neural networks, Wang H proposed a comprehensive error compensation method for multi-axis machine tools based on an improved BP-neural network algorithm (Wang, et al., 2017). They all introduced the importance of autonomous learning and the use of neural network algorithms to optimize it, but they did not conduct research on Japanese, nor did they improve their teaching system.

ALGORITHM NETWORK AUTONOMOUS LEARNING AND STUDENT TRAINING EDUCATION SYSTEM UNDER COMPUTER INTERACTION ENVIRONMENT

Human-computer Interaction

In computer user interface design, human-computer interaction technology is a very critical issue. It is closely related to disciplines such as ergonomics, cognition, and psychology. In simple words, it is the communication between people and computers, which includes the exchange of information between people and computers. With the development of computers, the computer has changed from a huge "cabinet" to a computer that can be held in the hand, as shown in Figure 1.



Jenny Spinning Machine perforated paper GUI interface

Figure 1: History of Human-Computer Interaction

Human-computer interaction has a wide range of applications, and gesture recognition is an important subject for human action recognition using mathematical operations. Its structure diagram is shown in Figure 2. The posture can be derived from any body movements or postures, but it is generally generated from the face or hands. Currently, the focus of the technology is on the recognition of faces and gestures. Users can control or interact with a device through a simple gesture without touching them (Kizilcec, et al., 2017; Goradia & Bugarcic, 2017). The recognition of posture, gait and human behavior is also the subject of gesture recognition technology. Gesture recognition can be seen as a way for computers to understand human language, thereby building a richer bridge between machines and humans than raw textual user interfaces or even GUIs (Graphical User Interfaces).

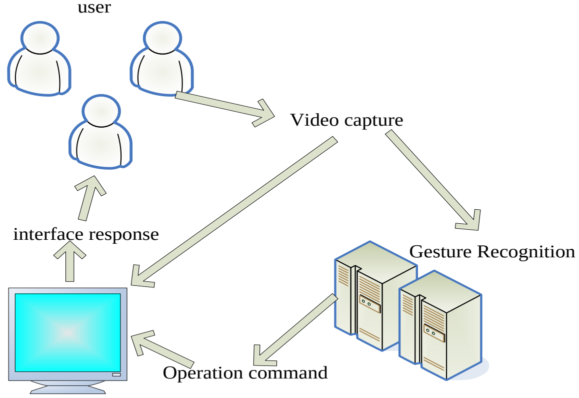


Figure 2: Schematic diagram of human-computer interaction structure

Self-learning Neural Network Algorithm

Neural networks are evolved from biological neurons, which are composed of neurons at different levels, as shown in Figure 3. Among them, the most mature and widely used is the reverse neural network, which uses the connections between a large number of nodes in the network to realize the information processing and classification of the network (Aldholay, et al., 2018). In this era of rapid development of education, those who can quickly master educational information and learn technology will have a better future. How to apply it to the field of neural network on the basis of the existing good research is a new subject.

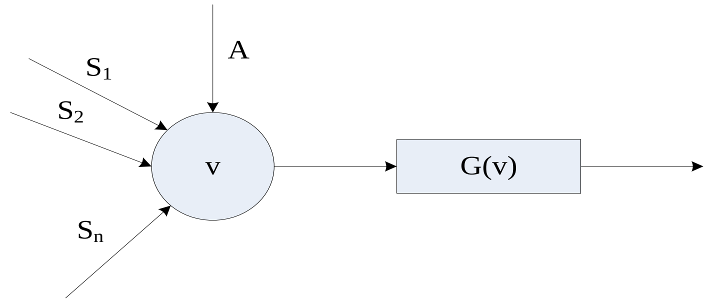


Figure 3: Schematic diagram of neurons

(1) Self-learning neural network

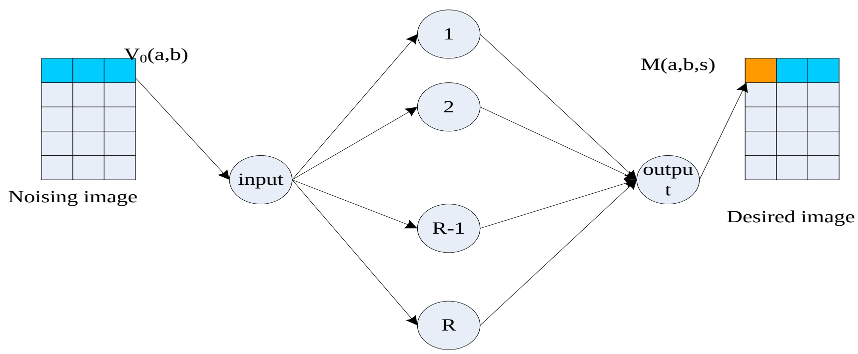


Figure 4: Multiple layers of neurons (single hidden layer)

The BP neural network has the advantages of simple structure and wide application range. The schematic diagram of its single hidden layer structure is shown in Figure 4.

After determining the purpose of learning, it is necessary to find a suitable learning goal. The way of learning determines the purpose of learning, then the purpose of learning is to achieve one's own purpose, and the way of learning will also be multiplied with half the effort (Balls, et al., 2018; Broadbent, 2017).

(2) ALBP algorithm

The iterative training and derivation process of the ALBP algorithm is as follows:

Its derivative is:

$$g^{l}(a) = g(a) * (1 - g(a)) \tag{1}$$

The activation function takes the derivative of the output layer neuron node:

$$g^{l}(net_r) = g(net_r) * (1 - g(net_r)) = e_r * (1 - e_r) \tag{2}$$

The activation function is derived from the hidden layer neuron nodes:

$$g^{l}(net_i) = g(net_i) * (1 - g(net_i)) = b_i * (1 - b_i) \tag{3}$$

Hidden layer neuron i output:

$$b_i = g\left(\sum_{j=1}^{n} s_{ji} a_j - \beta_i\right) = g(net_i) \tag{4}$$

Hidden layer neuron r output:

$$e_r = g\left(\sum_{j=1}^{m} u_{ir} a_i - \varphi_r\right) = g(net_r) \tag{5}$$

The output layer neuron error is computed by a squared error function based on the desired output versus the actual output:

$$Z = \frac{1}{2}\sum_{l=1}^{q}(d_l - e_l)^2 = \frac{1}{2}\sum_{l=1}^{q}\left(d_l - g\left(\sum_{i=1}^{m} u_{il} b_i - \varphi_j\right)\right)^2 \tag{6}$$

There is an intrinsic relationship between the output layer neuron output e_r and the corresponding weight u_{ir} .

$$\frac{\eta Z}{\eta e_r} = \frac{1}{2}\frac{\eta\sum_{l=1}^{q}(d_l - e_l)^2}{\eta e_r} = \frac{1}{2}\sum_{l=1}^{q}\left(-2(d_l - e_l) * \frac{\eta e_l}{\eta e_r}\right) = -(d_r - e_r) \tag{7}$$

The neurons in the output layer take the derivative of the weights:

$$\frac{\eta e_r}{\eta u_{ir}} = \frac{\eta e_r}{\eta net_r} * \frac{\eta net_r}{\eta u_{ir}} = g^l(net_r) * b_i \tag{8}$$

The error function adjusts the weights by derivation of the neurons in the output layer:

$$\frac{\eta Z}{\eta u_{ir}} = \sum_{l=1}^{q}\frac{\eta Z}{\eta e_l} * \frac{\eta Z}{\eta e_r} = \frac{\eta Z}{\eta e_r} * \frac{\eta e_r}{\eta u_{ir}} = -(d_r - e_r) * g^l(net_r) * b_i \tag{9}$$

There is no relationship between neurons in the same layer:

$$\frac{\eta e_r}{\eta b_i} = \frac{\eta e_r}{\eta net_r} * \frac{\eta net_r}{\eta b_i} = g^l(net_r) * \frac{\eta net_r}{\eta b_i} = g^l(net_r) * u_{ir} \tag{10}$$

$$\frac{\eta b_i}{\eta s_{ji}} = \frac{\eta b_i}{\eta net_i} * \frac{\eta net_i}{\eta s_{ji}} = g^l(net_i) * a_j \tag{11}$$

The error function adjusts the weights by derivation of the neurons in the hidden layer

$$\frac{\eta Z}{\eta s_{ji}} = -\sum_{r=1}^{q}(d_r - e_r) * g^l(net_r) * u_{ir} * g^l(net_r) * a_j = \sum_{r=1}^{q}\mu_r u_{ir} g^l(net_r) * a_j \tag{12}$$

Output layer neuron error signal:

$$\mu_r = (d_r - e_r) * g^l(net_r) = (d_r - e_r) * e_r * (1 - e_r) \tag{13}$$

Hidden layer neuron error signal:

$$\varepsilon_i = g^l(net_i) * \sum_{r=1}^{q} \mu_r u_{ir} = \sum_{r=1}^{q} \mu_r u_{ir} * b_i * (1 - b_i) \tag{14}$$

When the initial learning rate of network randomization is relatively small, the speed of weight adjustment will be relatively slow, and the network convergence speed will be very slow. When the random initial learning rate is relatively large, the weight adjustment speed will be quite fast, and the network may skip the global optimal value and fall into the local extreme value (Pardo, et al., 2016; Liu, 2017). Therefore, the ALBP algorithm adds a tightness variable to the adjustment of the weights. The tightness variable of the hidden layer is α, and the tightness variable of the output layer is λ. The change of the specified tightness variable value is as follows:

$$\alpha = \begin{cases} 0.85 & \mu_r(j) < \mu_r(j+1) \\ 1.15 & \mu_r(j) > \mu_r(j+1) \end{cases} \tag{15}$$

$$\lambda = \begin{cases} 0.85 & \lambda_i(j) < \mu_i(j+1) \\ 1.15 & \lambda_i(j) > \mu_i(j+1) \end{cases} \tag{16}$$

ALBP algorithm hidden layer to output layer weight adjustment:

$$u_{ir}(r+1) = u_{ir}(r) + \lambda * \Delta u_{ir} = u_{ir}(r) + \lambda * \alpha \mu_r b_i \tag{17}$$

Adjustment of the weights from the output layer of the ALBP algorithm to the hidden layer:

$$s_{ji}(r+1) = s_{ji}(r) + \alpha * \Delta s_{ji} = s_{ji}(r) + \alpha * \alpha \eta_i a_j \tag{18}$$

(3) Learning rate

The learning rate is set up to find the global optimum and prevent the network from falling into a local minimum. The ultimate goal is to make the network achieve the best classification prediction accuracy, and its role is to continuously adjust the weights during the network training process. Generally speaking, during the simulation experiment, the learning rate is set to χ. If the learning rate is too small, the network will converge very slowly during iterative training; however, if the learning rate is relatively large, the network will converge very quickly, and the classification accuracy of the network cannot be guaranteed, and the learning and training will lose its meaning (AbouOmar, et al., 2022).

The learning rate of the traditional algorithm is a value between the value range $(0,1)$ obtained by researchers for many years of research experience. If the value is 0 or 1, the algorithm will eventually fail to converge. If the value is a fixed value between $(0,1)$, the convergence speed of the iterative training is very slow at the beginning, and the later stage of the iterative training. Because the step size of the algorithm convergence is too large, it is easy to cause the algorithm to oscillate, and the iterative training falls into a state of local convergence. Therefore, researchers have proposed a variety of methods to improve the learning rate. The standard is to set a fixed value of χ_0 first, and during the experiment, update the weights and output errors in the network. It is found that the error is large when the network uses χ_0, and the negative $\Delta\chi$ is reduced by χ_0, and the network continues to be iteratively trained. If the network error becomes smaller and falls into a local minimum, it means that the learning rate used in the last iterative training is too small, and a positive $\Delta\chi$ is given and increased by χ_0 to increase the learning rate. As long as a suitable $\Delta\chi$ is selected, the network will get good classification accuracy without getting trapped in local minima, and the iterative training speed is also suitable (Gu, 2021; Qu, 2021).

Studies have shown that adaptive learning rates significantly improve the learning speed of the network. But adaptive learning rate During the learning process, the learning rate of the hidden layer and output layer neurons remains the same. Generally speaking, the local gradient of the neurons in the hidden layer is smaller than that of the neurons in the output layer, so the learning rate of the neurons in the hidden layer should be larger, so as to ensure that the learning speed of each neuron in the network is similar. Therefore, this paper slightly improves the adaptive learning rate: the learning rate of the hidden layer and output layer neurons is automatically adjusted as the error of the network changes. The initial value of the learning rate γ of the neurons in the output layer is greater than the initial value of the learning rate of the neurons in the hidden layer χ (Dang, et al., 2022).

Hidden layer neuron learning rate χ adaptive adjustment formula:

$$\chi(i+1)=\begin{cases}0.9\chi(i) & Z(i+1)>1.1Z(i)\\ \chi(i) & other\\ 1.1\chi(i) & Z(i+1)<0.9Z(i)\end{cases} \tag{19}$$

The output layer neuron learning rate γ adaptive adjustment formula:

$$\gamma(r+1)=\begin{cases}0.9\gamma(r) & Z(r+1)>1.1Z(r)\\ \chi\gamma(r) & other\\ 1.1\gamma(r) & Z(r+1)<0.9Z(r)\end{cases} \tag{20}$$

EXPERIMENTS ON NETWORK AUTONOMOUS LEARNING AND STUDENT TRAINING EDUCATION SYSTEM IN THE ENVIRONMENT OF HUMAN-COMPUTER INTERACTION

Experimental Design

(1) Questionnaire design

The investigation includes: Student gender, Japanese proficiency, final exam results, online teaching platform username. The second section has 34 options. W1-W20 mainly investigates the composition of autonomous learning ability in the network environment, W21-W34 investigates the needs of college students for online learning and the current situation of the Japanese teaching system (Wenjuan, 2021; Smys, et al., 2017).

(2) Purpose and object

In order to better understand the autonomy and autonomy of Japanese learners in the network environment, and to establish an educational system that is conducive to improving autonomy, this paper selects college students who teach Japanese in university campuses as the experimental object. Based on the Japanese major class, this study selected 400 college students as a sample by cluster random sampling. Through interviews, some things can be better understood.

(3) Questionnaire process

A questionnaire was prepared, and relevant expert opinions were consulted and revised. It conducts pre-surveys, revises the questionnaires, and finally completes printing. Then, an on-site investigation was launched immediately, and random sampling was carried out to determine the investigation object, also the scope of the investigation, and the results of the investigation. There were 400 questionnaires, and 380 were recovered, with a recovery rate of 95%. There were 360 valid questionnaires, with an effective rate of 90%. The recovery rate and efficiency of the survey results all meet the requirements of scientific research standards. The questionnaires were carefully checked, sorted out and surveyed, and the data were input using SPSS, Excel, etc., and SPSS software was used to test the data, and conduct statistics and analysis. In early December, this article selected 40 students who participated in a questionnaire survey and collected their interview results.

Using SPSS13.0 statistical software, descriptive analysis, T test, chi-square test and other methods were used for statistical analysis and processing of the collected data.

Survey Results

In terms of Japanese scores, 68 students achieved excellent results, accounting for 18.9%, reaching 279.

The frequency of college students logging on the Japanese online learning platform every week was 2.69, of which 36% of the college students logged on the Japanese online platform twice, and 21% of the college students logged on the Japanese online platform 3 times.

Students spend an average of 1.75 hours studying Japanese online, with 32% logging in for 1 hour, 29% for 2 hours, and 10% for 3 hours.

The five dimensions from W1 to W19 were assigned, among which, strongly disagree is 1, disagree is 2, unsure is 3, agree is 4, and strongly agree is 5. The statistical results are shown in Figure 5:

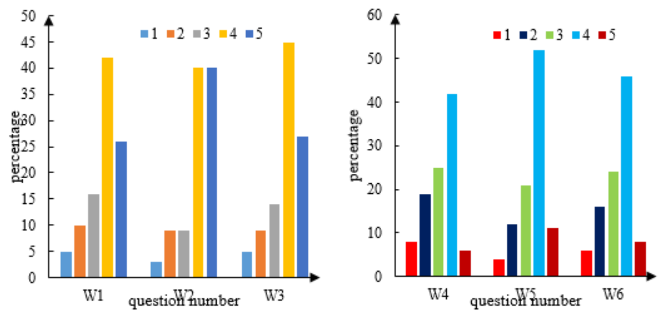


Figure 5: Percentage of choices for each item in terms of self-motivation

As can be seen from Figure 5, W1 refers to a part of self-ability: 69% thought they could learn Japanese well, and 15% thought they could learn Japanese well, 16% had no clear choice. W2 is part of the attribution propensity: 80% of Japanese students believe that learning Japanese depends on acquired effort is very important, 11% disagree with this view, and 9% express uncertainty. The targeting properties of W3 are well known: 72% see Japanese as a skill to improve future work research, 14% disagree and 14% have no clear choice. The learning interests of W4 are well known: 48% felt that the current way of learning Japanese online was interesting, 27% disagreed, and 25% were unclear. W5-W6 is a question about learning attitude: The homework assigned by the teacher could not be completed conscientiously, 63% of the classmates could do it conscientiously, and 21% of the classmates were unclear, and 54% of people agree that teachers can also conduct independent learning when they go out, 22% of them disagree, and 24% of them are not sure.

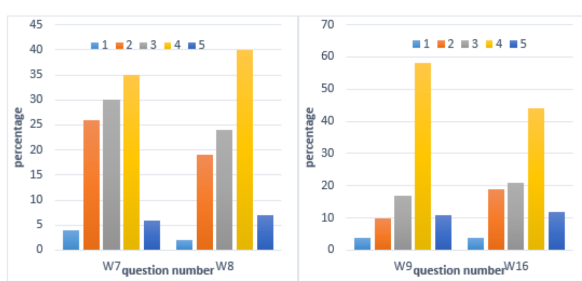


Figure 6: Percentage of options for each item in terms of learning planning ability

As can be seen from Figure 6, W7, W9, and W16 are the completion rates of the plan. 30% of Japanese students said they did not persevere in Japanese language teaching, 41% felt they could, and 30% were not sure. 16% of students could not complete online teaching proactively and on time, while 69% of students were able to complete online teaching proactively and on time, 17% had no clear choice. 58% of Japanese students said, "In Japanese learning, they often regret that they did not prepare well in advance and spend more time studying", only 23% said they would not have such a problem, and 21% said they would not Know. W8 stands for Establishing a Learning Purpose. 21% of students did not establish a clear short-range learning goal, 64% of students can determine their own short-range learning goals on the basis of learning tasks, and 15% of students do not have clear learning goals.

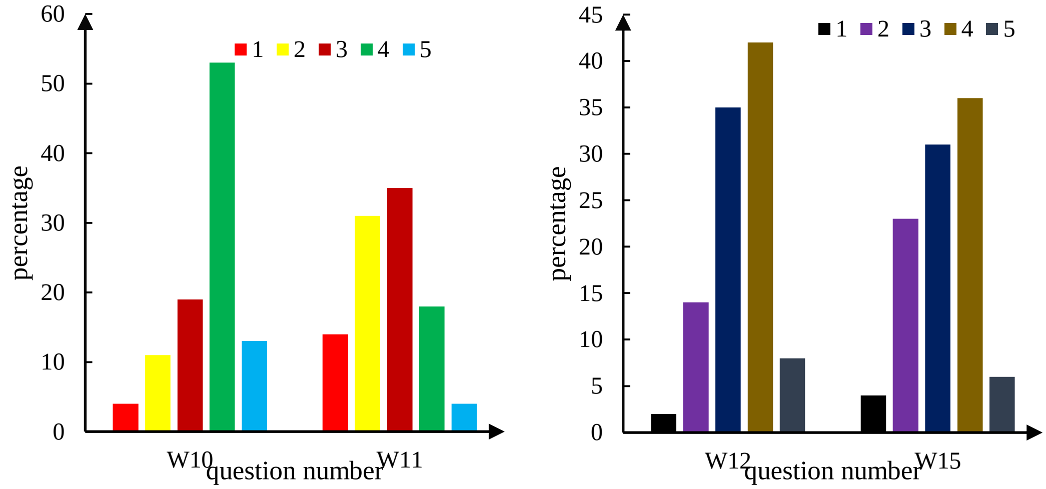


Figure 7: Percentage of options for each item in information processing ability

It can be known from Figure 7 that W10 and W11 are related to network operation and resource acquisition. About 15% of Japanese college students said that they could not quickly find the required Japanese materials through the Internet, 66% believed that they had this knowledge, and 19% did not have a clear understanding. About 44% of students said they couldn't quickly search and read pages about Japanese on the web, 21% said they could, and 35% didn't have a clear answer. It is well known that W12 and W15 are strategic aspects of online teaching. 16% of college students have differences in listening, speaking, reading, and writing, and cannot adopt corresponding teaching methods. 49% believed they could, 35% didn't have a clear answer, and 27% felt they were incapable of putting their newly acquired knowledge into practice. Only 43% felt they could consciously apply their newly acquired knowledge to practice. Additionally, 31% had no clear choice.

Table 1. Percentage of options for each item in cognitive ability

Options Question number	**W13**	**W14**	**W17**
1	4	6	3
2	28	28	18
3	16	21	30
4	42	38	42
5	10	7	7

As can be seen from Table 1, W13 is regarded as the management and monitoring of time. 52% of the respondents believed that their English expressions were in line with their real situation, and 32% of the respondents believed that the Japanese they learned did not match what they usually learn, 15% of respondents did not have a clear option. W14 is a monitoring related to the learning process. 34% of students have to do things that have nothing to do with their studies while surfing the Internet, only 45% of the respondents think they can do it, and 22% of the respondents are not sure. W17 is associated with self-assessment. 22% of the subjects failed to summarize the successful experience in time after the test, and analyzed the reasons and made corresponding adjustments. 48% of the students were able to sum up their successful experience in time after the exam, analyze the reasons for it, and make timely adjustments.

Table 2. Percentage of options for each item on communication and cooperation skills

Options Question number	**W18**	**W19**
1	9	11
2	24	29
3	26	33
4	35	23
5	6	4

As can be seen from Table 2, both W18 and W19 are about using tools to communicate. 33% of students believe that online communication enables them to communicate completely freely with teachers and classmates. 41% believe it, 26% of respondents did not have a clear option, 27% of students said they prefer to express their opinions in Japanese than before. Among them, 40% hold objections and 33% disagree.

Table 3. Statistics on the proportion of choices when encountering difficulties in learning

Options Question number	**W20**	
	number of people	**proportion**
ABC	40	11
ACB	29	8
BAC	14	4
BCA	90	25
CAB	25	7
CBA	162	45

As can be seen from Table 3, it is known that W20 is about communication and cooperation awareness. The order of choice of students is as follows: 11% of students choose ABC, 8% of students choose ACB, 4% of students choose BAC, 25% of students choose BCA, 7% of students choose CAB, 45% of students choose CBA.

A is to ask classmates or teachers for advice; B is to find relevant texts by yourself; C is to search for information on the Internet to find ways.

W21-W24 are surveys of online Japanese learning:

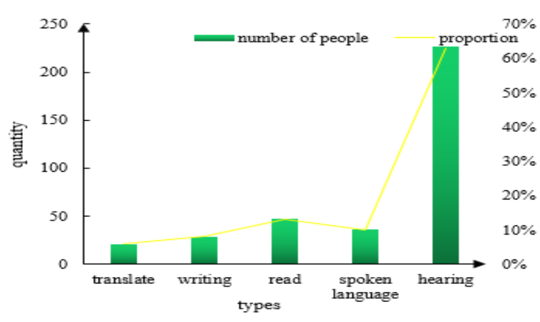


Figure 8: Statistical percentage of the best results for using the Internet to learn that Japanese skill

As can be seen from Figure 8, it is known that W21 and W22 are investigations on the effect of online Japanese learning. The percentage of students who believe that using the Internet to learn Japanese skills is the best choice: 6% for translation, 8% for writing, 13% for reading, 10% for speaking, and 63% for listening.

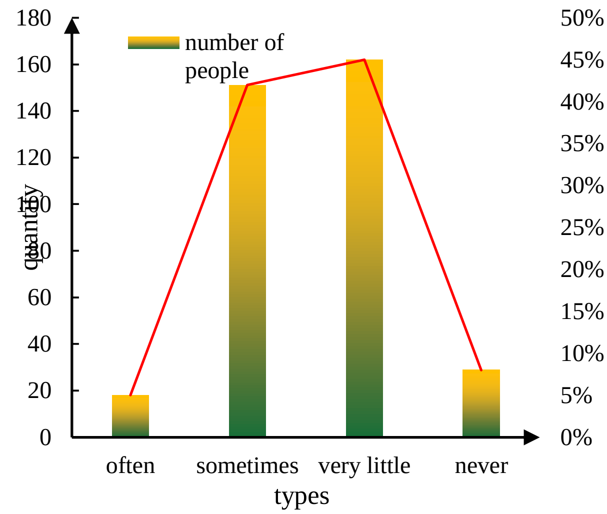


Figure 9: Statistical percentage of whether to visit other Japanese learning websites after class to learn Japanese

As can be seen from Figure 9, it is known that W23-24 is a survey of extracurricular learning. 5% of the students often learn Japanese online or use auxiliary software to learn Japanese, of which 42% can, 45% can only, and 8% never know.

W25-31 is a survey of college students' evaluation of online Japanese learning platforms:

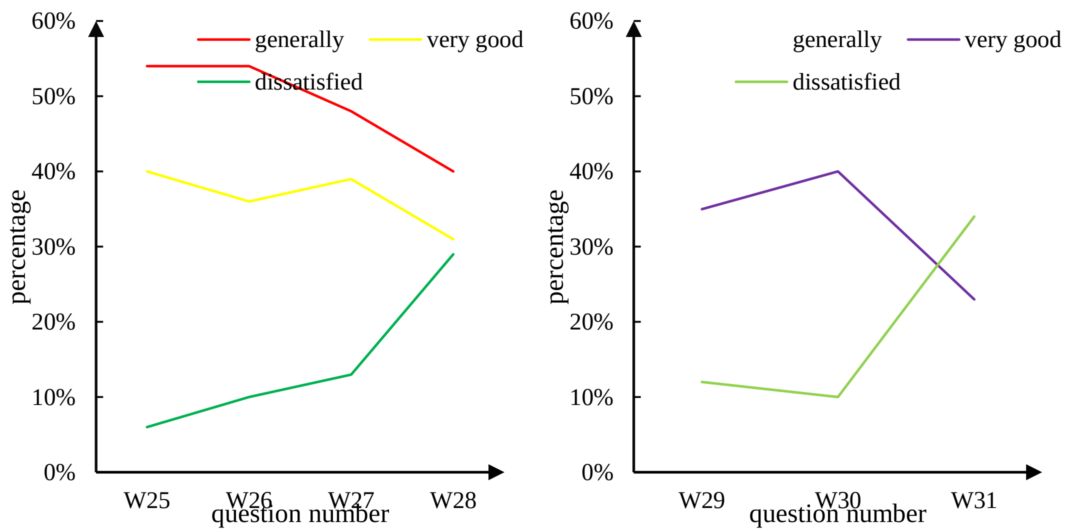


Figure 10: Survey of College Students' Evaluation of Online Japanese Learning Platforms

As can be seen from Figure 10, W25 involves the design of the interface: 54% think it's okay, 40% think it's good, 6% think it's bad. W26 deals with interaction design: 54% think it's OK, 36% think it's OK, and 10% think it's not good. W27 deals with connectivity: 48% of respondents said it was ok, 13% said it was not satisfied and 39% said it was ok. The speed of the W28's response is well known: 29% were very dissatisfied, 40% were satisfied, and 31.1% were satisfied. W29 is used in question answering systems: 53% think it's good, 12% feel uncomfortable, and 35% think it's good. The W30 is known for its wealth of resources: 12% are dissatisfied, 51% are okay, and 40% are good. The W31 is a well-known rating system: 34% were dissatisfied or very dissatisfied, 43% thought it was OK, and 23% thought it was OK.

Table 4. Requirements of online Japanese teaching system

What students hope to learn online		
Japanese culture	187	52%
Japanese test	172	48%
Japanese Learning Strategies	169	47%
Links to Japanese Sites	154	43%
other	24	6%

As can be seen from Table 4, the Japanese learning materials that students hope to obtain from the university online Japanese teaching system are Japanese culture (52%), various Japanese exams (48%), and Japanese learning strategies and methods (47%), recommendations and links to excellent Japanese learning websites (43%), and the proportion of students choosing this is about half.

Generally speaking, students have a good Japanese learning foundation and can have a clear understanding of the purpose of Japanese learning, but from the analysis of the results of the questionnaire survey, the situation of college students using the Japanese online teaching system is not satisfactory. Most students are unable to make a reasonable Japanese study plan and lack time management and monitoring of the learning process. Learning strategies use and awareness and ability to self-evaluate and communicate and cooperate. The surveyed students' overall evaluation of the multiple indicators of the online Japanese teaching system for college students is generally average, and continuous improvement is needed to meet the needs of the majority of students for independent Japanese learning.

Construction and Improvement of Network Teaching System Platform

The effect of students' autonomous learning in the network environment is inseparable from many factors. In addition to establishing the correct self-learning motivation and mastering the network self-learning strategy, the external network teaching management and network environment are all very important factors.

The school network center ensures the smoothness of the network, provides technical support and guarantee for the online Japanese teaching system, and strengthens the construction of hardware facilities. Quantitative management of the online teaching of Japanese teachers, that is, to put forward quality standards and specific quantitative requirements for online communication between teachers and students, answering questions and solving doubts, uploading Japanese materials, and online teaching research. The competent leaders and departments of online Japanese teaching should regularly or irregularly check the situation of teachers and students' independent teaching and learning of Japanese online. Teachers are organized to communicate with students to exclude various factors that affect the quality of Japanese online self-learning.

According to the results of the questionnaire survey and interview, the role of the Japanese online teaching system for college students in promoting students' autonomous learning needs to be strengthened. The learning evaluation system can be improved by enriching online learning resources. Measures such as learning support tools have been added to further improve the online Japanese teaching system for college students, so that it can play a better role, stimulate students' enthusiasm for independent Japanese learning in the online environment, and improve the effect of students' independent Japanese learning.

(1) Add a resource library system

For college students, the needs of society and the needs of future career development constitute their internal driving force for learning activities. The relevance and specificity of the learning content and needs can stimulate the learners' strong learning motivation and keep them lasting interest in the whole learning process. During the study period of college students, the main task is to advance along the professional direction and form a set of professional knowledge system. Therefore, in the content design of the network teaching system, attention should be paid to the combination of Japanese and majors, and to the improvement of Japanese application ability. In the selection of materials, various textbooks should be selected according to the preferences of students, so as to create a relaxed and pleasant Japanese online teaching atmosphere and create a Japanese learning atmosphere. It offers audio-visual online modules, Japanese broadcasts, and classic Japanese cartoons, enabling students to master Japanese-related entertainment, music, sports, and current affairs without knowing it.

(2) Add self-learning support tool system

This system mainly provides students with some self-learning aids, and teachers can also formulate learning evaluation forms for students' learning process, learning results, and application of learning strategies. The learning style scale can predict and analyze students' own learning tendencies and characteristics, and help students choose and formulate learning methods and learning plans that are more in line with their own learning styles and habits. The design purpose of the Japanese learning cognitive strategy guidance section is mainly to introduce the corresponding learning methods for the different problems encountered by students in Japanese learning. From the perspective of strategy training methods, it is mainly infiltration. Students find out their own shortcomings through self-analysis and diagnosis, click to read the relevant learning strategies, and further understand the methods, so as to carry out targeted exercises and practices to improve their Japanese level.

CONCLUSION

Under the guidance of autonomous learning theory and network learning theory, this paper analyzes the current situation of Japanese online teaching, and discusses the composition of autonomous learning under the network environment. This paper uses literature, questionnaires, interviews and other methods to study the autonomy of Chinese college students in the network environment. The research results of this paper show that in Japanese teaching, students' interest in autonomous learning in the network environment needs to be further strengthened, and there is still some discomfort in network learning, and the ability of autonomous learning needs to be improved. There are mainly the following problems: network teaching system: The resources on the online Japanese teaching system for college students are insufficient; the monitoring of students' online learning process needs to be improved; the response speed and learning evaluation system need to be improved, and the improvement of students' Japanese skills is uneven. In terms of the current situation of students' autonomous learning: the study plan formulated is not very maneuverable, and the plan cannot be completed well; the students lack time management and monitoring of the learning process, and the self-evaluation and adjustment ability needs to be improved; the communication and cooperation ability of the students needs to be improved.

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