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Online Self-learning Education of College Students Based on Human-computer Interaction Environment

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Abstract: This study aims to investigate the current situation and methods of online self-learning for college students in a human-computer interaction environment, with the objective of enhancing their autonomous learning abilities. The research methods include the introduction of metacognitive strategies, web crawler technology, and a network resource grouping model to address problems such as scattered learning materials and ineffective integration. The study also analyzes the existing issues faced by students in online self-learning, such as low learning efficiency, lack of direction, and weak information retrieval skills. The findings show that over 70% of college students do not have a clear understanding of their ability to learn independently online, while only 23% have mastered effective learning strategies. Additionally, 53% of students report difficulty in completing learning tasks efficiently without supervision. To address these challenges, the paper proposes the design of a learning management system with modules for online learning, performance assistance, and self-learning functionality. The research highlights the need for an integrated system to support students' autonomous learning and improve their learning outcomes through better resource management and enhanced guidance.

1. Introduction

With the development of science and technology, we have entered an era of big data based on the Internet and information technology. The use of multimedia and network technology in colleges and universities has become increasingly extensive and in-depth, and the learning methods of college students have also been enriched. More and more college students begin to use the network and its shared learning resources to conduct autonomous learning. However, in the face of massive information on the Internet, how to let students learn to learn and carry out meaningful learning is a problem that needs our attention and solution.

With the development of science and technology, information technology and network technology continue to mature, and people apply these mature technologies in the field of teaching to produce network teaching. It provides a very convenient and emerging way of education, so that learners can receive a good education without leaving home. According to the theory of educational personalization, different people have different knowledge bases, study habits and potentials. Therefore, according to the characteristics of learners, the types of learners are divided, aiming at different types of learners to analyze their autonomous learning modes and the problems they will encounter in autonomous learning, this paper seeks solutions according to the problems, which can effectively improve the efficiency and interest of learners in learning.

Metacognitive strategies help to develop students' self-management ability. It helps students find the most suitable learning mode for them, and the learning management system helps to monitor students' autonomous learning. It also provides learning strategies and learning tools. The innovation of this paper is that: (1) Based on meta-cognitive strategies to analyze the cognitive patterns and cognitive behaviors of college students, this paper studies the impact of meta-cognitive strategies on college students' online self-learning. (2) This paper manages and monitors the autonomous learning of college students by constructing a learning management system. Through personalized analysis of students, it provides students with learning materials and learning tools, and regularly conducts quizzes and analysis for students, etc.

2. Related Work

Many scholars have paid attention to the study of college students' online self-learning. Abigail J G used the electronic classroom as a learning tool for students to generate/collaborate content to study the current situation of college students' online self-learning, and believes that the electronic classroom is a good substitute for the traditional classroom. The authors argue that the availability of exploration time allows learning to keep pace with real-time while also providing an online community to share learning experiences [1]. Du Y designed the teaching process of self-learning with the help of flipped classroom, aiming to investigate the three dimensions of self-management learning ability, self-learning psychology and self-learning behavior of college students. The final experiment shows that the self-learning mode of college students based on flipped classroom can greatly improve the learning ability of college students [2]. Saraswati G used a qualitative interdisciplinary approach to analyze the relationship between digital literacy mastery and self-directed learning quality through case studies. The experimental results show that digital literacy plays a very important role in improving autonomous learning ability [3]. Aripova S studied the role of motivation in improving students' autonomous learning ability. The author believed that motivation plays a very important role in teaching and autonomous learning, and motivation can improve students' autonomous learning ability and academic performance to a certain extent [4]. However, these methods lack accurate models and large amounts of data to verify the accuracy of the results.

Metacognitive strategies and learning management systems can help improve students' autonomous learning ability and mobilize their enthusiasm for learning. Marantika J analyzed the relationship between metacognitive ability and learning autonomy to study how to improve students' autonomous learning ability. The results of the study show that there is a very significant correlation between metacognitive abilities, learner autonomy, and learning outcomes [5]. Gao C conducted research on students' autonomous learning based on mobile technology-assisted environmental law. Through survey analysis, the authors found that metacognitive strategies were the most frequently used strategies by respondents, students usually use metacognitive strategies to find the most suitable learning method for themselves and improve their ability to learn independently [6]. Wang Y combined "Internet +" with autonomous learning, based on the theory of multiple intelligences and the construction of autonomous learning systems to explore the impact of current learning tools and learning environments on students [7]. Herrera Y R provided a bibliographic analysis. The aim is to provide an epistemological approach to exploring the role of self-learning and learning management systems in higher education. This method facilitates students to form critical thinking [8]. But these studies are slightly lacking at the technical level.

3. Methods of College Students' Online Autonomous Learning Based on Human-computer Interaction Environment

3.1 Autonomous Learning under Metacognitive Strategies

(1) Metacognitive concept

The concept of "metacognition" belongs to the category of cognitive psychology, which is developed and extended from the research on "self-awareness" [9]. Metacognition consists of two parts: one is the static factor of consciousness, including knowledge component and motivational belief component. The other category is dynamic components, which mainly include metacognitive monitoring, control and regulation, which are organically unified in the individual. Static factors are the accumulation of dynamic factors and grow, modify and change due to the activities of dynamic factors [10].

Metacognition and autonomous learning are inseparable organic whole. Metacognition is the basis of autonomous learning, which is people's cognition of a series of internal activities such as their own learning status and learning situation. There is no doubt that metacognition is the core of autonomous learning, which provides internal motivation for autonomous learning, and the two influence each other and promote each other. Compared with traditional learning, autonomous learning in the network environment is more flexible and open, and has higher requirements for learners in all aspects [11-12].

Table 1. Metacognitive strategies that college students should have

Features of online self-learning	Students' learning	Meta-cognitive strategies required	Corresponding Cognitive Strategies
rich resources and mixed information	learning content and time allocation are difficult to grasp	self-directed learning according to learning needs	planning strategy
open network environment	a variety of learning situations and views are not unified	self-direction and self-management	monitoring strategy
weakening the role of teachers in guiding, supervising and managing	lack of systematic guidance and external supervision	monitor someone's own learning behavior	monitoring strategy
no systematic and objective evaluation mechanism	it is not clear whether the learning effect is good or bad	reflect on mistakes and correct them in time	evaluation strategy

From Table 1, it can be concluded that metacognitive strategies can help learners find the most suitable learning style, improve learning methods, monitor learning process, and evaluate learning effects in learning activities.

3.2 Self-learning Technology Based on Web Crawler

A web crawler is an internet robot. It can browse the information on the World Wide Web in an organized manner, in order to build a representative web index for these websites and information [13]. Web crawlers are also called web spiders, ants, or automatic crawlers. The web crawler selects a so-called seed URL from the URL collection and starts to visit its corresponding web page [14]. Because the crawler accesses these URL addresses, it can identify all the hyperlink addresses in the web page and add them to the URL address set. If the crawler can effectively archive and classify the website according to the webpage information copied and saved by itself, its efficiency can be further improved. The huge amount of website information makes the number of webpages downloaded by the crawler limited within the specified time, and the ultra-fast change frequency of website information makes some webpages updated or deleted quickly[15-16].

3.3 Grouping Algorithm of College Students' Online Self-learning Resources

Clustering mainly studies the internal connection between abstract data sets. It follows certain rules or methods to divide the source data into several categories to ensure that objects in the same cluster have similarities with each other, and the similarity with objects in other clusters is low[17]. The results obtained by clustering can clearly show the internal connection between abstract data, which lays a very necessary foundation for the discovery of knowledge [18-19]. Clustering is a frequently used data processing method to segment abstract datasets into similar classes of objects. The object class is also called a cluster, which is a collection of similar objects. Let E be the set of learning data, the object class is R, and it is a non-empty subset of E, then:

$$R_1 \vee R_2 \vee .... \vee R_m = E \tag{1}$$

$$R_i \wedge R_k = \varnothing (i \le m, k \le m, and, i \ne k) \tag{2}$$

Cluster analysis is divided into four steps:

a) Data preprocessing: it selects and extracts the features of the data, and determines the features of the random sample target object. Data feature selection is the most representative and important factor in extracting source data, which can directly affect the results of clustering. Data preprocessing also deals with some outliers.

b) Define the distance function: The definition of the distance function is also extremely important in the clustering process, because clusters are formed according to the similarity.

c) Clustering or grouping: It classifies different objects according to the similarity between the data.

d) Evaluation and output: Evaluation is another important stage for evaluating the results obtained by clustering and analyzing the results.

The distance function represents the distance between two data vectors. It maps a sample vector containing n attributes to a point in an n-dimensional space. It then represents the similarity between objects by some similarity between the vectors. Let $E(a,b) \ge 0$ be the distance formula, we get:

$$E(a,b) \ge 0 \tag{3}$$

$$E(a,b) = 0 \tag{4}$$

$$E(a,b) = E(b,a) \tag{5}$$

$$E(a,b) \le E(a,c) + E(c,b) \tag{6}$$

There are three types of distance functions commonly used in clustering algorithms:

1) Minkowski distance

$$E(a,b) = \sqrt[p]{\sum_{u=1}^{n} | a_u - b_u |^p} \tag{7}$$

P is a positive integer, if P=1, it represents the Manhattan distance:

$$E(a,b) = \sum_{u=1}^{n} | a_u - b_u | \tag{8}$$

If P=2, it means Euclidean distance:

$$E(a,b)=\sqrt[2]{\sum_{u=1}^{n}|a_u-b_u|^2} \tag{9}$$

In practical problems, the corresponding weight S may be assigned according to the importance of each attribute.

$$E(a,b)=\sqrt[p]{\sum_{u=1}^{n}S_u|a_u-b_u|^p} \tag{10}$$

The calculation of the Minkowski distance formula is not only relatively intuitive, but also more convenient and easy to understand, so it is mostly used in the practical application of calculating the acquaintance of sample objects [20]. There is a very obvious advantage in the Euclidean distance formula (when the parameter p=2). When the rectangular coordinate system undergoes orthogonal transformations such as translation or rotation, the Euclidean distance of the sample-mapped object remains unchanged, that is, the similarity of the objects is not changed. The disadvantage of the Minkowski distance formula is that it is greatly affected by the unit of the attribute variable. Therefore, when using the Minkowski distance formula, the units of each attribute variable should be kept consistent as much as possible.

2) Mahalanobis distance

$$E(a,b)=(a-b)^T\times\sum^{-1}(a-b) \tag{11}$$

Mahalanobis distance improves Minkowski's degree of influence by units, but its disadvantage is that it is not suitable for clustering algorithms with prior knowledge, and it is not suitable for large-scale data sets [21].

3) Reims distance

$$E(a,b)=\sum_{u=1}^{n}\left|\frac{a_l-b_l}{a_l+b_l}\right| \tag{12}$$

The Lance distance formula can overcome the influence of Minkowski distance in attribute variable units.

4. Experiment of College Students' Online Self-learning Based on Human-computer Interaction

4.1 Design and Implementation of Program

This paper investigates college students' online self-learning ability under the guidance of metacognitive strategies. On the basis of questionnaire survey, through online interviews, this paper analyzes whether students can consciously use metacognitive learning strategies to carry out autonomous learning in online autonomous learning. The content of the questionnaire includes students' majors, grades, genders, online study time, and problems and confusions they may encounter during online study. In the big frame, this paper adopts three dimensions of planning strategy, monitoring strategy and evaluation strategy to make the questionnaire. The dimension analysis of the questionnaire is shown in Table 2.

In this paper, students from Beijing Normal University were randomly selected, and 336 students in six classes from freshman to junior year were surveyed during the break time. A total of 330 valid questionnaires were collected.

Table 2. Dimensional analysis of metacognitive strategies

	Knowledge of metacognitive strategies	Use of metacognitive strategies
Planning strategy	set learning goals	prepare for study
	understand learning tasks and learning strategies	identify the problem to be solved
	analyze how to complete the learning task	plan study time and study tasks
Monitoring strategy	have monitoring awareness	monitor learning progress
	think about strategies to overcome obstacles	find problems and adjust it in time
	successfully complete learning tasks	ensuring the completion of learning tasks
Evaluation strategy	cognitive learning outcomes	evaluate and summarize the learning results
	evaluate the whole learning process	make attribution analysis

(1) Reliability test

In this study, the commonly used Cronbach α coefficient and half-score reliability were used as reliability indicators, and the statistical results are shown in Table 3.

Table 3. Scale reliability analysis

Dimension	Cronbach α	Split half reliability
Planning strategy	0.879	0.812
Monitoring strategy	0.913	0.898
Monitoring strategy	0.905	0.842
Total amount table	0.966	0.944

From Table 3, it can be concluded that the overall Cronbach alpha coefficient is 0.966, which exceeds 0.8, and the split-half reliability is 0.931, which also exceeds 0.8. It shows that the stability and internal consistency of the questionnaire are ideal and meet the measurement requirements.

(2) Content validity verification

Content validity reflects how well the content and behavior of the test match the predicted results. When designing the questionnaire, the content of the scale is systematically checked to determine whether the items written cover the range of the predictive concept. This questionnaire is to investigate the online self-learning ability of college students from the perspective of metacognition. The questionnaire is compiled from three dimensions: planning, monitoring, and evaluation. On this basis, this paper conducts in-depth communication with students through online interviews, and integrates the collected information into the questionnaire.

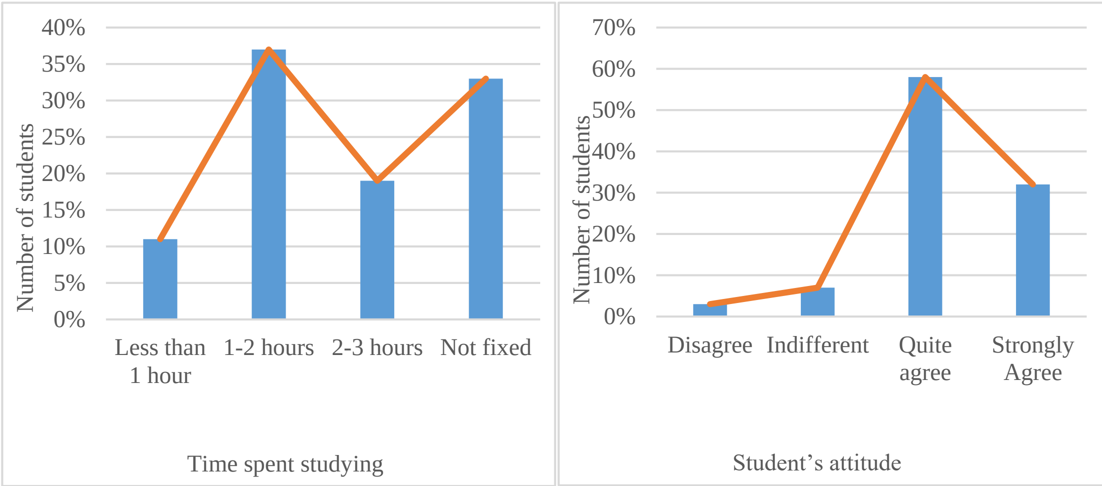
(3) Data analysis of basic information

In order to accurately evaluate the online self-learning ability of college students, this paper firstly investigates the current situation of college students' online self-learning. The following is a specific analysis of the data obtained from the relevant 6 questions.

The first module:

1) In response to the question "How long do you spend online every day for learning-related activities?", 37% of the students chose 1-2 hours, and 33% of the students chose not fixed time. 11% of the students chose less than 1 hour, and 19% of the students chose 2-3 hours, as shown in Figure 1(a). From the results, nearly half of the students study online for 1-2 hours a day, and 19% of students study online for 2-3 hours. Therefore, it can be seen that most students have the experience and needs of online learning, and this method of using online learning is common among college students.

2) In response to the question "Do you think that university study should not be limited to textbooks, teachers, and libraries, but should be obtained from as many sources as possible?", 32% and 58% of students chose the strongly agree and agree. Only 3% and 7% of the students chose disapproval and indifferent, as shown in Figure 1(b).



(a) Time spent on the Internet for learning-related activities (b) College students' attitudes towards obtaining resources from more sources

Figure 1. Survey results of the first module

Second module:

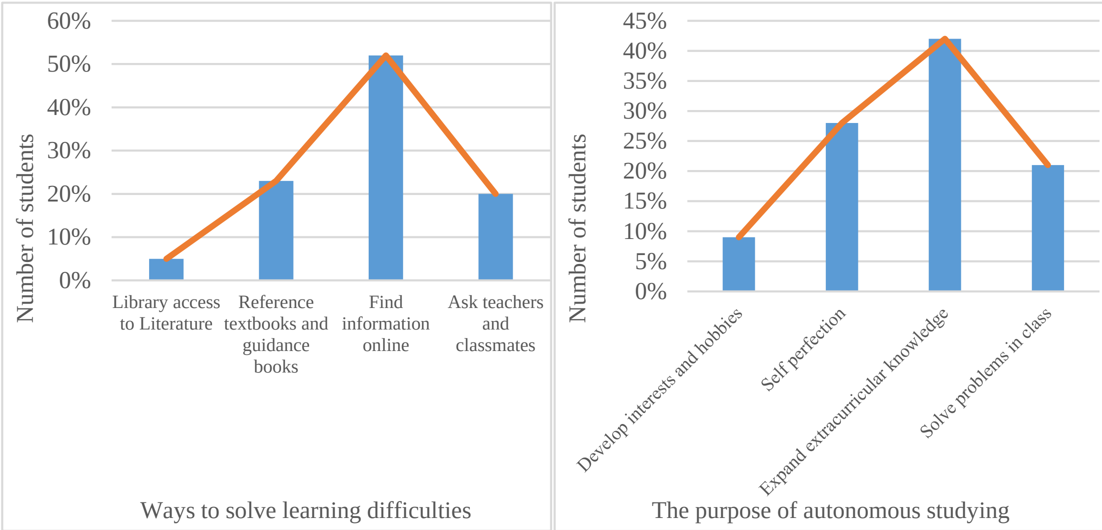
3) For the question "What is your usual solution to difficulties and problems in your studies?", 52% and 20% of the students respectively think that they will solve the difficulties and problems they encounter in their studies by searching for information on the Internet and consulting teachers and classmates. 23% and 5% of the students will refer to textbooks and tutoring materials and go to the library to check literature, as shown in Figure 2(a). It can be seen that the use of network resources has become an important way for college students to solve their learning problems.

4) In response to the question "What is the main purpose of your self-learning with the help of the Internet?", 42% and 21% of the students believe that the main purpose is to expand extracurricular knowledge and solve in-class problems. 28% and 9% of the students believe that the main purpose is to improve themselves and develop interests as shown in Figure 2(b).

The third module:

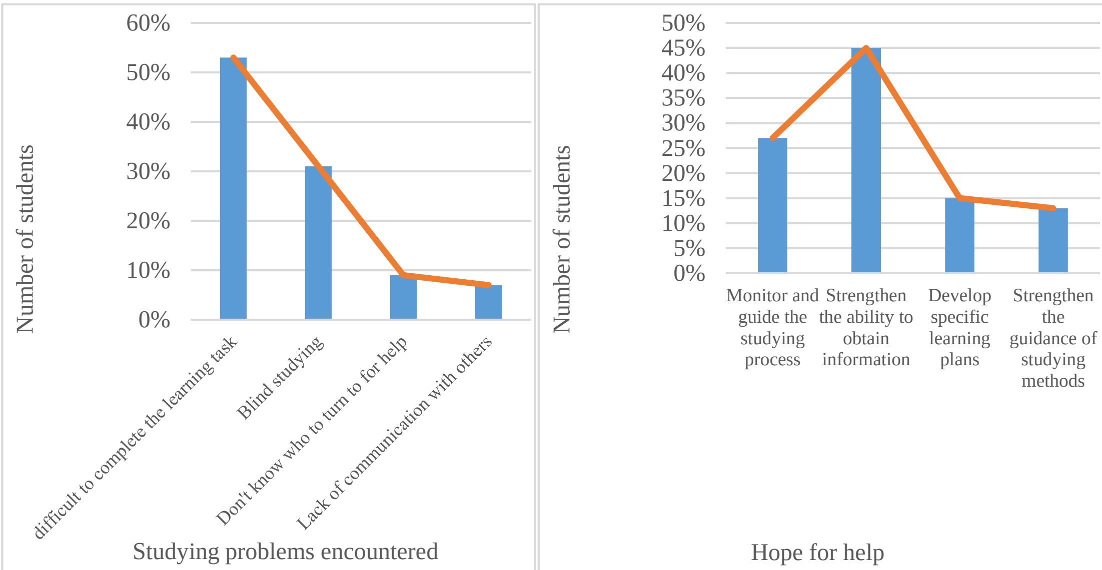
5) In response to the question "What do you think is the biggest problem encountered during online learning?", 53% of students think that it is difficult to complete the learning task efficiently without guidance and supervision. 31% of students think that they are not good at processing and filtering information, and their learning is relatively blind. 9% think that they do not know who to turn to when they encounter problems, and 7% of the students have communication problems and lack communication with others, as shown in Figure 3(a). It can be seen that there are still some problems in the online self-learning of college students. Nearly half of the students showed weak monitoring and management skills for learning, and more than one-third of students lacked preparation and planning skills.

6) In response to the question "What do you hope to get help with regarding the problems encountered in online learning?", 45% of the students needed help in obtaining information effectively. 27% of students want monitoring and guidance on their learning. 15% and 13% of the students, respectively, want help in developing specific study plans and strengthening the guidance of study methods, as shown in Figure 3(b).



(a) Difficulties encountered by students and their solutions (b) The purpose of online self-learning

Figure 2. Survey results of the second module



(a) The biggest problem encountered in online self-learning (b) Hope for help

Figure 3. Survey results of the third module

4.2 Cognitive Ability Level of College Students' Autonomous Learning

By studying the subject's cognition of self and online autonomous learning, cognition of online learning tasks and mastery of cognitive strategies, the investigation of metacognition knowledge is carried out. The data statistics are shown in Table 4.

Table 4. Statistical results of various dimensions of college students' online self-learning metacognitive ability

Scale dimension	Mean	sort	grand mean
Meta-cognitive knowledge	3.48	1	3.41
Meta-cognitive experience	3.41	2	
Meta-cognitive regulation	3.34	3	

It can be seen from Table 4 that the overall level of metacognitive ability of college students in the process of online self-learning is relatively good. College students' cognitive understanding of their own knowledge, knowledge of online learning tasks and knowledge of strategies has reached a certain standard level. On the whole, the metacognitive ability of college students is slightly insufficient, and it is necessary to improve it.

Table 5. The mastery of metacognitive knowledge of college students' online self-learning

	How to learn	Learning ability	Learning tasks	Learning effective strategies	Resource tools	Strategy application	Insufficient advantages
Incompatible	12.3%	15.6%	17.1%	24.3%	16.9%	11.6%	13.4%
Sometimes consistent	54.5%	61.9%	42.6%	52.7%	53.5%	57.6%	63.9%
Very consistent	33.2%	22.5%	40.3%	23.0%	29.6%	30.8%	22.7%
Mean value	3.21	3.44	3.58	3.32	3.59	3.62	3.50
Standard deviation	0.719	0.846	0.798	0.876	0.802	0.883	0.826

From Table 5, it can be concluded that 33.2% of college students fully understand how to study independently. It shows that most college students are more confident in solving problems through self-learning through the network, and they already have the knowledge of the network environment and the basic learning process under the network environment. For their own learning ability, 22.5% and 61.9% believe that they are completely consistent and sometimes consistent, indicating that 84.4% of college students have the ability to independently carry out online self-learning.

5. Conclusion

This paper draws the following conclusions: (1) Metacognitive strategies enhance students' autonomous learning and self-management abilities by helping them find the most suitable learning style. (2) 48% of students engage in daily autonomous learning, and 90% actively seek information beyond classrooms and libraries. (3) Over half of students turn to the internet for solutions and resources when facing difficulties, aiming to enrich their knowledge and improve skills. (4) The lack of guidance and supervision hinders learning efficiency, making it a key issue in autonomous learning. (5) Only 23% of students have effective learning strategies and self-awareness of their strengths and weaknesses. (6) A learning management system can address these challenges by monitoring and improving students' self-study efficiency. While the paper contributes to understanding online autonomous learning, it acknowledges limitations, such as the insufficient detail in the design of the learning management system. Future research should focus on refining this system.

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References

[1] Abigail J G, Lipin R. Students' Reflections on Pandemic Impacted Chemistry Learning[J]. Journal of Chemical Education, 2020, 97(9):3327-3331.
[2] Du Y. Study on Cultivating College Students' English Autonomous Learning Ability under the Flipped Classroom Model [J]. English Language Teaching, 2020, 13(6):13-13.
[3] Saraswati G, Areni G, Anellysha D. "Success is in your hand": Digital literacy to support students' autonomous learning in speaking class [J]. ELT Forum Journal of English Language Teaching, 2021, 10(1):70-78.
[4] Aripova S. Students' Motivation In Autonomous Learning[J]. Turkish Journal of Computer and Mathematics

Education (TURCOMAT), 2021, 12(4):1095-1098.
[5] Marantika J. Metacognitive ability and autonomous learning strategy in improving learning outcomes[J]. Journal of Education and Learning (EduLearn), 2021, 15(1):88-96.
[6] Gao C, Shen H Z. Mobile-technology-induced learning strategies: Chinese university EFL students learning English in an emerging context[J]. ReCALL, 2020, 33(1):1-18.
[7] Wang Y, Wang C. Study of the English Autonomous Learning Situation of College Freshmen in the "Internet Plus" Era[J]. Advances in Social Sciences Research Journal, 2019, 6(12):150-167.
[8] Herrera Y R, Moral P, García SA, Sánchez MLZ. Metacognition and autonomous learning in higher Education[J]. Revista Cubana de Educacion Medica Superior, 2018, 32(4):293-302.
[9] Logesh R, Subramaniyaswamy V. Learning Recency and Inferring Associations in Location Based Social Network for Emotion Induced Point-of-Interest Recommendation[J]. Journal of Information Science and Engineering, 2017, 33(6):1629-1647.
[10] Sun X, Basu A, Cheng I. Multi-Sensor Motion Fusion Using Deep Neural Network Learning[J]. International Journal of Multimedia Data Engineering and Management, 2017, 8(4):1-18.
[11] Jiang W, Ye X, Chen R, Su F, Huang S. Wearable on-device deep learning system for hand gesture recognition based on FPGA accelerator[J]. Mathematical Biosciences and Engineering, 2021, 18(1):132-153.
[12] Huang J, Liu B, Tao J. Learning long-term temporal contexts using skip RNN for continuous emotion recognition[J]. Virtual Reality & Intelligent Hardware, 2021, 3(1):55-64.
[13] Hwang W Y, Manabe K, Cai D J, Ma ZH. Collaborative Kinesthetic English Learning With Recognition Technology [J]. Journal of Educational Computing Research, 2020, 58(5):946-977.
[14] Ye W, Chen H. Human Activity Classification Based on Micro-Doppler Signatures by Multiscale and Multitask Fourier Convolutional Neural Network[J]. IEEE Sensors Journal, 2020, 20(10):5473-5479.
[15] Fritz A, Brandt W, Gimpel H, Bayer S. Moral agency without responsibility? Analysis of three ethical models of human-computer interaction in times of artificial intelligence (AI)[J]. De Ethica A Journal of Philosophical Theological and Applied Ethics, 2020, 6(1):3-22.
[16] Hu Z, Hu Y, Liu J, Wu B, Han, Dongmin, et al. 3D Separable Convolutional Neural Network for Dynamic Hand Gesture Recognition[J]. Neurocomputing, 2018, 318(NOV.27):151-161.
[17] Gyllen J G, Stahovich T F, Mayer R E, Darvishzadeh A, Entezari N. Accuracy in judgments of study time predicts academic success in an engineering course[J]. Metacognition and Learning, 2019, 14(2):215-228.
[18] Xu Y, Liu J, Zhai Y, Gan J, Labati RD. Weakly supervised facial expression recognition via transferred DAL-CNN and active incremental learning[J]. Soft Computing, 2020, 24(8):5971-5985.
[19] Lateef F, Ruichek Y. Survey on Semantic Segmentation using Deep Learning Techniques[J]. Neurocomputing, 2019, 338(APR.21):321-348.
[20] Ren F, Deng J. Background Knowledge Based Multi-Stream Neural Network for Text Classification[J]. Applied Sciences, 2018, 8(12):2472.
[21] Chau K Y, Law K M, & Tang Y M. Impact of Self-Directed Learning and Educational Technology Readiness on Synchronous E-Learning[J]. Journal of Organizational and End User Computing, 2021, 33(6), 1-20.