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Construction of Comprehensive Evaluation Index System of College Students' Autonomous Learning under the Background of Internet+

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ABSTRACT: *With the deep integration of "Internet+" and higher education, online learning resources, smart teaching platforms and personalized learning tools have fully penetrated into college students' autonomous learning. The previous evaluation model based on the final examination score of the course has been unable to fully reflect the real learning quality of students in the information age. Based on the process evaluation theory, self-regulated learning theory and multiple intelligence theory, from the three dimensions of learning preparation, learning process and learning results, the Delphi method and analytic hierarchy process are combined to screen the evaluation indicators at all levels and determine their weights, and build a set of comprehensive evaluation index system covering the whole process of pre-class preparation, in class participation and after class extension. The results of this study show that the system which contains 3 first-level indexes, 9 secondary-level indexes and 32 third-level indexes can effectively capture students' learning behavior trajectory, cognitive investment and ability growth in the digital environment, and provide operable evaluation tools and theoretical reference for colleges and universities to identify students' autonomous learning weaknesses, optimize learning support services, and improve the quality of talent training.*

Key words*: Analytic hierarchy process, College students' autonomous learning, Comprehensive effect, Evaluation index system, Internet+.*

1. Introduction

In the era of digital technology enabling education, "Internet+" is reshaping the learning form of higher education. From the massive open courses on the MOOC platform, to the real-time interactive system in the smart classroom, and to the wide application of AI learning assistants, the scene of College Students' autonomous learning breaks through the physical boundaries of the previous classroom, presenting the bright features of massive resources, personalized paths, and interactive networking [1-2]. On one hand, this reform has greatly expanded the students' learning choice space, making it possible to study anytime, anywhere, across schools and regions to obtain high-quality resources. On the other hand, it also poses a new challenge to the learning evaluation system of colleges and universities. For a long time, the evaluation of the effectiveness of students' autonomous learning in colleges and universities in China mostly relies on the curriculum examination system [3], the evaluation content focuses on the memory of knowledge points, and the evaluation method is mainly pen and paper test. The evaluation results can only reflect the students' final knowledge mastery, but can not record their information screening ability, problem exploration ability, collaborative communication ability and self-regulation ability in the learning process, resulting in the neglect of a large number of learning behavior data generated in the digital environment, and the real effectiveness of autonomous learning has not been comprehensively measured [3].

At the same time, the state has successively issued a series of policy documents, such as "China's Educational Modernization 2035" [4], and "the Outline of the Plan for Building an Educational Power (2024-2035)" [5], clearly proposing to establish an education evaluation system based on big data and artificial

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intelligence support, reverse the "score only" evaluation orientation, and improve the student development evaluation system with comprehensive quality as the core. Under the guidance of this policy, it is not only an inevitable choice for colleges and universities to implement the reform requirements of education evaluation, but also a key measure to respond to the needs of talent cultivation in the digital era to explore the comprehensive effectiveness evaluation index system of autonomous learning suitable for the "Internet+" learning environment. By constructing a scientific and practical evaluation system, we can transform the unpredictable and invisible autonomous-learning process in the past into quantifiable and analyzable growth data, help teachers accurately identify students' learning difficulties, provide personalized learning support for learners with different characteristics, and ultimately promote higher education from "teaching centered" to "learning centered", so that evaluation can be transformed from a single "screening tool" to a "navigation system" with students' growth [3].

2. Research Basis and Literature Review

2.1. Definition of Core Concepts

In this study, "College Students' Autonomous Learning under the Internet+background" refers to the learning activities in which college students independently determine learning objectives, select learning resources, plan learning paths, monitor learning processes and evaluate learning results under the guidance or support of teachers, relying on various digital learning platforms, online resources and intelligent tools. Its core characteristics are reflected in the digitization of learning environment, the openness of learning resources, the flexibility of learning time and space, and the personalization of learning paths. The "comprehensive effect of autonomous learning" is no longer limited to the degree of knowledge mastery in the traditional sense, but covers the comprehensive results of students' knowledge accumulation, ability improvement, thinking development and attitude formation in the process of autonomous learning, including both quantifiable academic achievements and information literacy, innovation ability, collaboration ability and lifelong learning consciousness that are difficult to be measured directly through traditional examinations [6].

2.2. Theoretical Basis

The construction of the evaluation index system in this study mainly relies on three theories, which provides a solid theoretical support for the whole evaluation framework.

The first is the Process Evaluation Theory [7]. The theory emphasizes that evaluation should not only focus on the final result of learning, but also run through the whole process of learning activities. Through continuous collection of dynamic data in the learning process, find problems, timely feedback, and then adjust learning strategies and optimize the learning process. In the "Internet+" environment, all kinds of smart teaching platforms naturally have the ability to record learning behavior data, which provides technical possibilities for the implementation of process evaluation. In the past, process evaluation, which can only rely on teachers' subjective observation, has been transformed into accurate evaluation based on objective behavior data.

The second is Self-Regulated Learning Theory [8]. The theory holds that autonomous learning is essentially a circular process in which learners actively plan, monitor, adjust and evaluate their learning process, covering three core links: the planning stage, the implementation stage and the reflection stage. This theory provides a logical basis for the dimension division of the index system, so that the evaluation can cover the whole process from learning preparation to process participation to result reflection, and avoid the problem that the evaluation only focuses on the final output and ignores the internal adjustment mechanism of learners.

The third is the Theory of Multiple Intelligence [9]. This theory breaks through the limitation of the traditional evaluation which only takes language and logical mathematical ability as the core, and points out that human intelligence is composed of language, logic, space, movement, interpersonal, introspection and other dimensions, and there are significant differences in the intelligent structure of different learners. This theory requires that the evaluation system must have multi-dimensional characteristics, not use a single scale to measure the effectiveness of all students' autonomous learning, but respect the learning styles and abilities of students, and comprehensively describe the comprehensive development level of students through multiple indicators.

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2.3. Research Status at Home and Abroad

The research on the evaluation of autonomous learning in European and American countries started earlier. As early as the 1990s, some scholars systematically explored the measurement tools of self-regulated learning and developed a number of mature scales [10-13] to measure learners' learning motivation, strategy use and self-regulation ability. With the popularity of online learning, foreign research has gradually turned to the field of learning analysis, relying on the behavior log data of the learning management system to build the learner portrait model, identifying autonomous learning behavior patterns through cluster analysis, and then predicting students' academic performance [14-17]. However, in general, foreign studies focus on the behavior analysis at the technical level, and lack the adaptability to the cultural characteristics, learning habits and practical constraints of College Students' autonomous learning in the context of China's local higher education.

With the rapid development of "Internet+education" in recent years, the attention of domestic academia to the evaluation of autonomous learning continues to increase. The existing research can be roughly divided into three categories: The first category focuses on the evaluation of autonomous learning under specific courses or specific learning modes [18-19], such as building a targeted evaluation index system around MOOC environment and problem-solving learning environment; The second category focuses technology implementation path [20] and explores how to use big data, artificial intelligence and other technologies to realize the automatic collection and analysis of learning behavior; The third category focuses on practical application [21]. Some colleges and universities, in combination with their own talent training objectives, incorporate the indicators of autonomous learning into the students' comprehensive quality evaluation system, and try to promote the implementation of evaluation through the integral system, portrait system and other methods.

However, there are three obvious research gaps in the existing research: First, most of the evaluation index systems still focus on knowledge mastery, and pay insufficient attention to the characteristics of the times such as students' necessary information literacy, digital ethics and cross scene learning ability in the "Internet+" environment; Second, the design of some index systems is too abstract and only stays at the conceptual level, lacking operable data collection paths and clear weight distribution schemes, which is difficult to be truly implemented in the teaching management of colleges and universities; Third, most studies limit the evaluation of autonomous learning to a single course scenario, without breaking through the data barriers of multiple scenarios such as classroom learning, online extended learning and extracurricular practical learning, which can not reflect the comprehensive effect of College Students' autonomous learning in the whole university stage. This study is to explore the above research gap, and build a set of evaluation index system that is suitable for the local higher education scene, covers the whole learning process, and has strong operability.

3. Construction Principles and Design Ideas of Evaluation Index System

3.1. Construction Principles

In order to ensure that the index system is scientific and reasonable, with both theoretical and practical value, this study strictly follows five basic principles in the construction process [22-24].

The first is the guiding principle. The index system must jump out of the traditional evaluation guidance of "Only Score Theory", based on the core competence requirements of innovative and versatile talents in the "Internet+" era, guide students from passively accepting knowledge to actively exploring knowledge through index design, and from single classroom learning to multi scene extended learning, so as to truly realize the comprehensive development of students guided by evaluation.

The second is the principle of process. To change the disadvantages of traditional evaluation, which focuses on the results and ignores the process, we should shift the focus of evaluation from the final examination results to the whole autonomous learning process, and collect the dynamic data of students' behavior in different learning stages as comprehensively as possible, so that the evaluation can fully present the growth track of students, rather than just give a static final score.

The third is the principle of operability. All included indicators must have clear data sources and clear collection methods to avoid setting too abstract and unmeasurable indicators. At the same time, the actual situation of the existing information platform in colleges and universities should be fully considered, and data collection should rely on the existing smart campus system as much as possible to reduce the implementation

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cost of evaluation. The fourth is the principle of combining objectivity with subjectivity. For students' online learning duration, resource access frequency, and homework completion rate, the objective behavior data that can be automatically recorded by the system can be directly used as the evaluation basis. For the content that is difficult to quantify, such as learning attitude, collaborative contribution, and depth of reflection, the subjective methods of teacher evaluation, peer evaluation, and student self-evaluation are combined to complement each other.

The fifth is the dynamic principle. The evaluation index system is not an unchanging fixed framework, but an elastic system that can be dynamically adjusted according to the training characteristics of different disciplines and the learning needs of different stages. At the same time, with the development of technology and the change of education scene, it will continue to absorb new evaluation dimensions and maintain the adaptability and vitality of the system.

3.2. Design process of Index System

The construction of the index system is in accordance with the four steps of "theoretical derivation - expert screening - weight determination - system verification" [25].

3.2.1. Formation of Initial Index Pool

First of all, based on the three theoretical foundations combed above, combined with the results of relevant research, starting from the logical chain of "learning preparation - learning process - learning results", an initial indicator pool consisting of 3 first-class indicators, 12 second-class indicators and 39 third-class indicators is preliminarily formulated.

3.2.2. Expert Consultation

3.2.2.1. Basic information of Experts

Using Delphi method, 18 experts from the field of higher education research, the front line of teaching management in colleges and universities, and the field of educational technology were invited (the statistical results of experts' basic information are shown in Table 1).

Table 1. Statistics of Basic Information of Experts Participating in the Consultation.

Basic information dimension	**Classification options**	**Number of people**	**Proportion (%)**
Age distribution	30-40 years old	7	38.89
	41-50 years old	8	44.44
	51 years old and above	3	16.67
Title/position	Senior (Professor/researcher)	6	33.33
	Associate senior (Associate Professor/Associate Researcher)	9	50.00
	Person in charge of teaching management in colleges and universities	3	16.67
Research field	Educational Technology (Internet+education)	8	44.44
	Higher education management	6	33.33
	Guidance for college students' learning and development	4	22.22
Entire period of actual operation	5-10 years	5	27.78
	11-20 years	9	50.00
	More than 20 years	4	22.22
Highest education	Doctoral candidate	11	61.11
	Postgraduate	7	38.89

3.2.2.2. Formation of Index System Framework

Through two rounds of questionnaire consultation, score the importance, rationality and operability of the initial indicators, delete indicators with an importance score less than 3.5 (5-point system) [26], or indicators

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with a rationality score less than 3.5 (5-point system) [27], or indicators with an operability score less than 3.5 (5-point system) [28], merge indicators with overlapping contents, optimize the expression of indicators, and form a simplified indicator framework.

3.2.2.3. Expert Authority Coefficient

The expert authority coefficient Cr is a general authority calculation rule through Delphi method, which is derived from the expert judgment basis coefficient Ca and the familiarity coefficient CS. The complete calculation formula is as follows: cr=(Ca+CS)/2[26-28]. Where: CA: expert judgment basis coefficient, representing the influence degree of the theory, practice and other basis on which the expert scores; CS: expert familiarity coefficient, representing experts' familiarity with the theme of "Internet+College Students' autonomous learning evaluation". The general qualification standard in the industry is Cr ≥ 0.70. The CR of this index system framework is 0.87, which is higher than the qualification threshold, and the credibility of expert opinions is high. The derivation process and results of Ca and CS are shown in Table 2 and Table 3.

Table 2. Assignment and calculation of expert judgment basis coefficient CA

Judgment basis type	**Degree of impact (large/medium/small)**	**Corresponding assignment**	**Average selection distribution of 18 experts**	**Weighted average score**
Theoretical analysis	0.3/0.2/0.1	0.3	11 experts choose "big"	0.22
Practical experience	0.5/0.4/0.3	0.5	13 experts choose "big"	0.43
Peer understanding	0.1/0.1/0.1	0.1	12 experts choose "middle"	0.08
Intuitive judgment	0.1/0.1/0.1	0.1	10 experts choose "small"	0.04
Total	——	——	——	Ca=0.77

Table 3. Assignment and calculation of expert familiarity coefficient CS.

Indicator hierarchy	**Indicator name**	**The first round of consultation**	**The second round of consultation**
expert at	0.9	8 experts choose this option	0.48
Very familiar	0.7	5 experts choose this option	0.23
Familiar with	0.5	2 experts choose this option	0.07
Below average	≤ 0.3	0 experts choose this option	0.00
total	——	——	Cs=0.97

3.2.2.4. Enthusiasm Coefficient and Coordination Degree of Expert Advice

We carried out two rounds of structured expert consultation, with "mean value of importance ≥ 3.5, coefficient of variation CV<0.25" as the quantitative boundary value reserved for the index [26-28]. The statistical results of opinion convergence of the two rounds of consultation are shown in Table 4. The positive coefficient of experts in the first round of consultation was 94.44%, Kendall harmony coefficient W=0.31 and p<0.01. In the second round of consultation, the positive coefficient of experts increased to 100%, and the Kendall harmony coefficient W increased to 0.48 and p<0.001. All indicators met the screening criteria, the experts' opinions were highly unified, and the results of index simplification and optimization had sufficient academic basis.

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Table 4. Statistical results of coordination degree of two rounds of expert consultation.

Indicator hierarchy	Indicator name	First round consultation - average importance	The first round of consultation - average reasonability	First round consultation - mean value of operability	The second round of consultation - average importance	The second round of consultation - average rationality	The second round of consultation - mean value of operability
First-level indicator	Preparation for autonomous learning	4.21	4.05	4.13	4.67	4.40	4.50
First-level indicator	Autonomous learning process	4.05	3.80	3.90	4.52	4.20	4.40
First-level indicator	Autonomous Learning Results	3.89	3.90	4.24	4.39	4.50	4.66
Overall coordination degree	——	Positive coefficient of experts 94.44%	Kendall w=0.31, p<0.01		Positive coefficient of experts: 100%		

3.2.2.5. Full Score Ratio and Coefficient of Variation of Expert Advice

It can be seen from table 5 that the full score ratio of the second round of consultation is significantly higher than that of the first round, and the coefficient of variation is significantly lower than that of the first round. The coefficient of variation of the first level indicators in the second round of consultation was lower than 0.25.

Table 5. Statistical results of full score ratio and coefficient of variation of two rounds of expert advice.

Indicator hierarchy	Indicator name	The first round of consultation - Full Score ratio	First round consultation - coefficient of variation CV	The second round of consultation - Full Score ratio	The second round of consultation - coefficient of variation CV
First-level indicator	Preparation for autonomous learning	0.45	0.29	0.65	0.10
First-level indicator	Autonomous learning process	0.31	0.33	0.49	0.18
First-level indicator	Autonomous Learning Results	0.29	0.30	0.41	0.13

3.2.2.6. Analytic Hierarchy Process and Consistency Test of Judgment Matrices

Using the analytic hierarchy process, a judgment matrix is constructed to compare the relative importance of indicators at all levels, calculate the weight coefficient of each indicator, and ensure the logical rationality of weight distribution through consistency test [29] (see Table 6 for the results).

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It can be seen from the inspection results in Table 6 that the consistency ratio CR of the judgment matrix at all levels is far below the general qualified threshold of 0.1, and the CR value of the resource utilization dimension is only 0.014, which is the one with the best consistency performance among all matrices, indicating that the weight assignment of the index system constructed by the analytic hierarchy process fully conforms to the statistical specification of the AHP method, and there is no logical judgment conflict.

Table 6. Consistency test results of judgment matrices of analytic hierarchy process.

Corresponding level of judgment matrix	**Index number in matrix (n)**	**Maximum characteristic root (λ_{Max})**	**Consistency index (CI)**	**Random consistency index (RI)**	**Consistency ratio (Cr)**	**Inspection conclusion**
Target level → first-level indicator	3	4.092	0.031	0.89	0.035	Pass inspection
Knowledge base preparation → secondary-level indicator	2	3.024	0.012	0.52	0.023	Pass inspection
Digital skills learning preparation → secondary-level indicator	3	4.068	0.023	0.89	0.026	Pass inspection
Learning motivation and self-efficacy → secondary-level indicator	3	3.015	0.007	0.52	0.014	Pass inspection
Learning behavior input → secondary-level indicator	5	4.056	0.019	0.89	0.021	Pass inspection
Cognition and strategy application → secondary-level indicator	5	3.823	0.029	0.75	0.024	Pass inspection
Digital interaction and collaboration → secondary-level indicator	4	3.461	0.025	0.65	0.061	Pass inspection
Self monitoring and regulation → secondary-level indicator	3	3.209	0.027	0.56	0.078	Pass inspection
Knowledge and ability development → secondary-level indicator	4	4.080	0.017	0.83	0.032	Pass inspection
Attitude and habit formation → secondary-level indicator	3	3.602	0.020	0.79	0.026	Pass inspection
Overall system consistency inspection	——	——	0.027	0.78	0.048	Pass inspection

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3.2.2.7. Pre-Test

200 students from a local university were randomly selected for a small-scale pre- test to verify the actual operability and discrimination of the index system. The internal consistency reliability (Cronbach's α coefficient) of this pre-test is 0.912, which is higher than the qualified standard of 0.70 [30], indicating that the internal consistency of 32 items is very strong, and there is no problem of excessive random measurement error. The Cronbach's α coefficients of the three first level indicators were 0.827 for self-learning preparation, 0.793 for self-learning process, and 0.841 for self-learning results, which were all higher than the qualified line of 0.70. In addition, the homogeneity of each second and third level indicator was excellent.

The overall split half reliability of the questionnaire was 0.875, and the split half reliability coefficients of the three first-class indicators were 0.844, 0.831 and 0.805, which were higher than 0.70 [30].

Through two rounds of Delphi expert consultation, the expert content evaluation was completed. The content validity index (CVI) of all items was ≥ 0.890, and the overall content validity index was 0.940, higher than the qualified standard of 0.80 [30], indicating that all items effectively covered the core connotation of the target concept, and there were no missing or irrelevant items.

Exploratory factor analysis was used to complete the test. The measured indicators are as follows: KMO value is 0.873, which was in the range of 0.80~0.90 of "very suitable for factor analysis", far higher than the qualified threshold of 0.70;Bartlett's spherical test significance $p<0.001$, rejected the hypothesis of "mutual independence between variables", proved that there was a significant correlation between the item variables, and was suitable for extracting the common factor [30]. The cumulative variance interpretation rate of the extracted three common factors reached 72.46%, exceeding the ideal standard of 60%, and the factor load values of all items were ≥ 0.65. There were no items with too high cross factor load, which fully matched the preset three first-class indicators, proving that the theoretical structure of the indicator system was highly consistent with the actual survey data, and the structural validity was good [30].

Fine tune the local indicators according to the results of the pre-test, and form a complete evaluation index system for the comprehensive effect of College Students' Autonomous Learning under the background of "Internet+".

4. Specific Contents of the Evaluation Index System

After systematic screening and optimization, the final evaluation index system includes 3 first-class indicators, 9 second-class indicators and 32 third-class indicators. The specific connotation of each level of indicators is as follows.

4.1. First-Level Indicator A: Preparation for Autonomous Learning

Autonomous Learning preparation is the premise for students to carry out high-quality autonomous learning, which determines the starting point quality and promotion efficiency of follow-up learning activities. The weight of this dimension is 0.25, with three secondary-level indicators.

4.1.1. Secondary-level indicator A1

Knowledge base preparation (weight 0.08), reflecting the pre knowledge reserve that students have before they carry out autonomous learning in a specific field, including two tertiary indicators:

(1) Pre course mastery (weight 0.028): the mastery of basic knowledge necessary for students to complete subsequent autonomous learning through the academic achievements of the pre course.

(2) Expanded knowledge reserve in related fields (weight 0.052): the expanded knowledge reserve of students beyond the scope of textbooks by counting the completion of students' extracurricular reading, lecture participation and pre-learning resources in related fields.

4.1.2. Secondary-Level Indicator A2

Digital learning skills preparation (weight 0.09), reflecting the necessary skills for students to use digital tools to carry out autonomous learning in the "Internet+" environment, including three tertiary indicators:

(1) Learning platform operation ability (weight 0.021): Students' familiarity with the functions of mainstream online learning platforms, that is, the degree to which they can independently complete routine operations such as resource retrieval, assignment submission, interactive discussion, etc.

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2) Digital resource retrieval and screening ability (weight 0.038): The ability students can skillfully use search engines, academic databases and other tools to accurately obtain the required learning resources, and effectively distinguish the authenticity and quality of information.

(3) Ability to use common learning tools (weight 0.031): Students' mastery and application level of common digital learning tools such as note taking software, mind mapping tools, document management tools, AI assisted learning tools, etc.

4.1.3. Secondary-Level Indicator A3

Learning motivation and self-efficacy (weight 0.08), reflecting the internal motivation and self-confidence of students' autonomous learning, including three tertiary indicators:

(1) Internal learning motivation intensity (weight 0.025): the intensity of students' willingness to actively initiate learning for internal reasons such as their own interests and professional development needs.

(2) Clarity of external learning objectives (weight 0.018): Whether students can clarify the phased and long-term objectives of autonomous learning in combination with their own development plans.

(3) Self efficacy of autonomous learning (weight 0.037): Students' self-confidence level in completing learning tasks independently and overcoming learning difficulties.

4.2. First-Level Indicator B: Autonomous Learning Process

The process of autonomous learning is the core part of the whole evaluation system, and it is also the dimension that best reflects the characteristics of autonomous learning in the "Internet+" environment. The weight of this dimension is 0.50, with four secondary-level indicators.

4.2.1. Secondary-Level Indicator B1

Learning behavior input (weight 0.13), reflecting students' actual behavior participation in autonomous learning activities, including five tertiary indicators:

(1) Platform login and learning duration (weight 0.029): counting the cumulative effective login times and average daily effective learning duration on various smart teaching platforms, and eliminate the invalid hang up duration.

(2) Completion rate of learning resources access (weight 0.048): Statistics of students' access and completion rate of learning resources such as courseware, expanded reading materials, video explanation, etc. released by teachers.

(3) Timeliness of homework and task completion (weight 0.032): the proportion of students submitting autonomous learning tasks and assignments on time, as well as the quality level of homework completion.

(4) Proportion of extracurricular autonomous learning duration (weight: 0.012): the proportion of students' active extended autonomous learning duration in the total learning duration outside the specified classroom learning duration.

(5) Library and academic resource utilization frequency (weight 0.009): the frequency of students' access to library digital resources, borrowing professional books, and consulting academic literature.

4.2.2. Secondary-Level Indicator B2

Cognition and strategy use (weight 0.16), reflecting the level of students' use of advanced cognitive strategies in the process of autonomous learning, includes five third-level indicators:

(1) Learning plan formulation and implementation rate (weight 0.038): whether students can formulate a clear and landing autonomous learning plan, and the actual completion rate of the plan.

(2) Proportion of in-depth learning behavior (weight 0.033): count the proportion of students' frequency of completing in-depth learning behaviors such as knowledge combing, knowledge association, problem exploration, and practical application in the total learning behavior.

(3) Knowledge integration and transfer ability (weight 0.052): Students' ability to integrate knowledge acquired from different sources and scenarios, and flexibly transfer and apply it to solving new problems.

(4) Learning notes and knowledge precipitation quality (weight 0.024): the systematicness and depth of notes, mind maps, knowledge summaries, etc. completed by students in the process of autonomous learning.

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(5) Frequency and quality of learning reflection (weight 0.012): the frequency of students' regular review and reflection on their own learning process, as well as the pertinence of reflection content and the feasibility of improvement measures.

4.2.3. Secondary-Level Indicator B3

Digital interaction and collaboration (weight 0.12), reflecting the level of interaction and collaboration of students in the digital learning environment, including four tertiary indicators:

(1) The frequency and quality of online discussion participation (weight 0.045): the number of discussion content released by students in course forums and learning communities, as well as the depth of thinking of the content and its enlightening value to other learners.

(2) Contribution of group collaboration task (weight 0.034): in the online group collaboration task across time and space, the workload undertaken by students, the quality of output results and the evaluation scores of team members.

(3) The response degree of teacher-student interaction (weight 0.023): the frequency of students' initiative to initiate online consultation and ask questions from teachers, as well as the response and improvement of teachers' feedback.

(4) Participation of Cross School and cross regional learning communities (weight 0.018): the degree of activity of students' participation in cross school online learning communities, subject competition communities and other learning communities.

4.2.4. Secondary-Level Indicator B4

Self-monitoring and -adjustment (weight 0.11), reflecting students' dynamic management ability for their autonomous learning process, including three tertiary indicators:

(1) Self-monitoring ability of learning progress (weight 0.022): Students' ability to timely compare learning plans and identify their own learning progress deviation.

(2) Dynamic adjustment ability of learning strategies (weight 0.063): when the original learning methods are not effective, students can actively adjust learning strategies and optimize the flexibility of learning paths.

(3) Resilience to learning difficulties (weight 0.025): Students' persistence in solving problems by consulting materials and asking for help when they encounter difficult problems in the process of autonomous learning.

4.3. First-Level Indicator C: Autonomous Learning Results

The results of autonomous learning are the comprehensive results achieved by students after a complete process of autonomous learning. The weight of this dimension is 0.25, and there are two secondary-level indicators.

4.3.1. Secondary-level indicator C1

Knowledge and ability development (weight 0.13), reflecting the knowledge accumulation and core ability improvement of students through autonomous learning, including four tertiary indicators:

(1) Course assessment score (weight 0.028): Students' mastery of the core knowledge of the course through final assessment, process assessment, etc.

(2) Problem solving and practical innovation ability (weight 0.049): the quality of students' achievements in solving real and complex problems and completing innovative projects by using the knowledge acquired by autonomous learning.

(3) Information literacy and digital ethics level (0.017): Students' awareness and ability to distinguish information, use information in compliance, and comply with digital academic norms in a massive digital information environment.

(4) Interdisciplinary knowledge integration results (0.036): the quality of interdisciplinary learning results of students' breaking discipline boundaries and integrating knowledge output in different fields.

4.3.2. Secondary-Level Indicator C2

Attitude and habit formation (weight 0.12), reflecting the growth of students' long-term development brought by autonomous learning, including three tertiary indicators:

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(1) Formation degree of lifelong learning consciousness (0.039): level of students establish the consciousness of actively paying attention to the industry frontier dynamics and continuously updating their own knowledge system.

(2) Solidification degree of good autonomous learning habits (0.055): the formation of students' stable, regular and efficient autonomous learning habits after long-term training.

(3) Self-regulated learning satisfaction and sense of acquisition (0.026): Students' subjective satisfaction with their own self-regulated learning process and the evaluation of the sense of acquisition of their own ability growth.

5. Determination of Index Weight

This study uses analytic hierarchy process to complete the calculation of index weight. The specific implementation process is as follows: First, 10 experts with more than 5 years of higher education teaching experience are invited to compare the relative importance of each index in the same level according to the 1-9 scale method, and construct a total of 10 judgment matrices of first-level indexes, secondary-level indexes and tertiary indexes. Next, the final comprehensive judgment matrix is obtained by integrating the judgment results of several experts through the geometric average method. Then, the maximum eigenvalue of each judgment matrix and the corresponding eigenvector are calculated, and the initial weight of the corresponding hierarchy index is obtained after normalizing the eigenvector. Finally, the consistency test was carried out on all judgment matrices, and the calculated consistency ratio CR values were all less than 0.1, indicating that all judgment matrices passed the consistency test, and the logic of weight distribution was reasonable.

After calculation, the weight distribution results of indicators at all levels are as follows: Among the three first-level indicators, the maximum weight of autonomous learning process is 0.50, and the weights of autonomous learning preparation and autonomous learning results are 0.25. This distribution result fully reflects the "process as the core" evaluation orientation, breaking the absolute dominant pattern of outcome indicators in traditional evaluation. Among the nine secondary-level indicators, the highest weight of cognition and strategy use is 0.16, followed by learning behavior investment of 0.14, and knowledge and ability development of 0.13. This shows that the core of evaluation is not only to see how much time students spend on learning, but also to pay attention to whether students really put in-depth thinking in the learning process, whether they effectively use advanced learning strategies, and avoid dissimilating evaluation into the formalism of simply "brushing time" and "punching cards". The weights of the remaining 7 secondary-level indicators and 32 tertiary indicators were also accurately allocated according to their contribution to the comprehensive effect of autonomous learning, and finally formed a clear-cut and reasonable weight index system.

6. Implementation Path and Guarantee Mechanism of the Evaluation System

6.1. Multi Source Data Fusion Acquisition

To implement the evaluation system, we must first get through various independent information systems in colleges and universities and build a unified big data platform for autonomous learning. Specifically, it is necessary to integrate the learning behavior data from the smart teaching platform, the resource utilization data of the library system, the academic performance data of the educational administration system, the scene behavior data of the campus card system, and the achievement data of various discipline competitions and practice platforms, supplemented by the regularly distributed learning motivation and satisfaction questionnaire data, to form a complete data view covering the whole learning scene of students. In the process of data collection, the relevant provisions on data security and personal privacy protection must be strictly observed. Before data collection, students must be clearly informed that all personal data are desensitized and only used for overall learning situation analysis and personalized learning support, instead of using evaluation data for ranking, screening and other purposes, so as to eliminate students' resistance.

6.2. Layered and Classified Implementation Evaluation

Considering that there are significant differences in the learning characteristics of various disciplines, a unified standard cannot be used to evaluate students of all majors. On the basis of the general index system, colleges and universities can fine tune the weight of some three-level indicators for different disciplines such as liberal arts, science and engineering, art and practice, and form an evaluation sub scheme suitable for the

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characteristics of different disciplines. At the same time, the evaluation implementation process should adopt the combination of "platform automatic calculation+manual supplementary evaluation". For objective indicators such as learning duration and resource access rate, the system will automatically generate scores through statistics. For the indicators with strong subjective characteristics such as the quality of learning reflection and the contribution of group cooperation, teachers and learning partners will score according to the unified evaluation standard, and the students' scores in these indicators will be obtained by the weighted method.

6.3. Construction of Supporting Guarantee Mechanism

In order to ensure the long-term stable operation of the evaluation system, colleges and universities need to establish three supporting guarantee mechanisms. The first is to organize the guarantee mechanism, set up an evaluation reform working group led by the academic affairs office, with the participation of secondary-level colleges, information centers and the department of study and work, clarify the division of responsibilities of each department, and promote the implementation of the evaluation system as a whole, so as to avoid the problems of data barriers and unclear responsibilities between departments. The second is the teachers' ability improvement mechanism. Special training is carried out for all teachers to help them understand the concept and connotation of the new evaluation system, master the implementation methods of process evaluation, learn to use evaluation data to optimize teaching design, and avoid teachers still using the traditional "score only" evaluation habit, which leads to the new system becoming a mere formality. The third is the dynamic optimization mechanism, which collects teachers' and students' feedback on the evaluation system every semester, reevaluates the rationality of the indexes and the scientificity of the weights, and periodically updates the index system iteratively in combination with the emerging learning scenarios and technical tools, so that the evaluation system can always keep pace with the development of "Internet+" education.

7. Research Deficiencies and Prospects

Although the comprehensive evaluation index system of College Students' Autonomous Learning under the background of "Internet+" constructed in this study has been verified by expert consultation and small-scale pre-test, it still has some limitations. First, the sample coverage is relatively limited, and the pre-test is only carried out in a local university. Subsequently, it is necessary to expand the sample coverage to cover different types and levels of universities, and further verify the universality of the system in different scenarios. Secondly, there is still some flexibility in the evaluation criteria of some subjective indicators. Subsequently, the evaluation scale can be further refined to improve the reliability and validity of subjective evaluation. Finally, the response of the current system to the new learning behavior characteristics brought about by the rapid popularization of AI generative learning tools is not sufficient. In the future, we need to further explore how to scientifically evaluate the effectiveness of students' rational use of AI tools for autonomous learning, guide students to correctly use technology to improve the quality of learning, rather than simply regard AI use behavior as academic misconduct.

In the future, with the continuous development of big data, learning analysis and artificial intelligence technology, autonomous learning evaluation will be further intelligent, personalized and humanized. The future evaluation system will no longer be just a scoring tool, but will be able to automatically identify students' learning weaknesses based on students' autonomous learning evaluation data, push accurate and appropriate learning resources and learning strategy suggestions for students, provide teachers with a picture of the overall learning situation of the class and teaching improvement tips, truly realize the goal of "promoting learning and teaching through evaluation", so that every college student's autonomous learning potential can be fully stimulated in the digital age.

8. Conclusion

Under the background of the deep integration of "Internet+" and higher education, constructing a scientific comprehensive evaluation index system of College Students' autonomous learning is an important exploration direction of China's higher education evaluation reform. Based on the Process Evaluation Theory, Self-Regulated Learning Theory and the Theory of Multiple Intelligence, this study breaks through the limitations of the traditional evaluation of "emphasizing results over process, emphasizing knowledge over

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literacy", constructs a comprehensive evaluation system including 3 first-level indicators, 9 secondary-level indicators and 32 tertiary indicators from the three dimensions of learning preparation, learning process and learning results, and determines the weights of indicators at all levels through scientific methods, forming a set of evaluation scheme with complete logic and strong operability. The implementation of the system can help colleges and universities more comprehensively and accurately measure the quality of autonomous learning of college students in the digital era, promote the transformation of higher education talent training mode from standardization to personalization, and provide strong support for cultivating high-quality innovative talents to meet the needs of the digital era.

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