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A Bayesian inference-based model for evaluating the effect of ecological education in the process of study tour activities in national parks

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ABSTRACT

In recent years, the development of study activities is in full swing. In order to study the eco-education effect in national park study activities, this paper introduces Bayesian network and constructs an eco-education effect assessment model based on Bayesian inference. In the comparison of the absolute error of the assessment value with other assessment models, the assessment accuracy of the Bayesian inference assessment model in this paper is obtained. After constructing the ecological education effect assessment index system and completing the assignment, the level of ecological education that should be achieved in the national park study activities is obtained through Bayesian inference diagnosis. Finally, according to the results of education effect assessment, the probability of each indicator being in various states is obtained by simulation using Monte Carlo method. The mean absolute error of the Bayesian assessment model is 0.26 points, which is smaller than other comparative assessment models and has the highest assessment accuracy. The model's ecosystem principles, anthropogenic intervention impacts, ecological disasters and ecological protection measures should be guaranteed to reach 75.6, 64.8, 67.9 and 69.4. The ecological operation rules (59.4→79.8), climate change (50.6→70.2), biodiversity reduction (52.2→69.8), and pollution prevention and control (56.4→78.3) have the highest accuracy for the ecosystem principle, anthropogenic intervention impacts, ecological disasters and ecological protection measures, respectively. , anthropogenic intervention effects, ecological disasters and ecological conservation measures, and ecological education effects had the greatest impact. The overall score of ecological education effect was 84.1, and the scores of ecosystem principle, human intervention impact, ecological disaster and ecological protection measures were 83.8, 85.2, 83.0 and 84.2.

Keywords: bayesian inference, assessment model, Monte Carlo method, ecological education

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1. Introduction

"Integrating ecological civilization education into the whole process of educating people is an important mission of education to serve the great rejuvenation of the Chinese nation." The National Park is rich in plant resources and a wide variety of species, which provides rich practical materials for the ecological study program [1-3]. Students can observe and study the biological taxa in the scenic area in close proximity, and realize the dialectical relationship between diversity and unity of living systems [4]. The rich ecological resource materials in the park can effectively test and enhance students' ecological cognitive level. Through fieldwork, observation, research, and scientific thinking and analysis, students are able to discover valuable biological problems, analyze problems by using the concept of life, and select tools to verify conjectures, enhance scientific inquiry ability, and cultivate methods of dealing with ecological relationships between human beings and nature and ecological practice skills [5-7]. There are safe and mature hiking tourist routes in the National Forest Park, so students can experience the impact of tourists on the ecological environment and form correct ecological ethics and consumer values [8-9].

In the modern context of study, emphasis is placed on the journey itself, where learning occurs amidst the tour.The study course under the perspective of ecological protection is even farther away from the classroom, according to the characteristics of the activity place for practical education, the popularization of ecological knowledge, but ignored the children's education of ecological protection awareness, or too much inclined to practical experience, the phenomenon of only travel but not learning [10-12].

With the gradual expansion of the organization and participation of study travel activities, many regions have achieved some results in the practice of study travel [13]. However, there persist some notable issues in the process of research and study travel, which undermine the desired effectiveness of the activities, rendering their impact less than optimal and their efficiency still inadequate [14]. On the one hand, the phenomenon of "merely traveling without learning" prevails in research and study travel activities [15]. Some schools have developed a habit of adopting a hands-off approach during the development process, relying solely on travel agencies to recommend research products and routes. As a result, these research activities often lack substance, with simplistic objectives and content that fail to impart significant educational value. Students are merely "guided" through the itinerary, resulting in low enthusiasm and minimal learning outcomes. Consequently, the quality of these activities diminishes significantly, and the overall effect is far from satisfactory [16-17]. On the other hand, there is also the phenomenon of "only learning but not traveling" in study tours. When organizing study tours, some schools put too much emphasis on letting students go out with their academic tasks, neglecting students' personal feelings and experiences in nature and society [18-19]. Before departure, the subject teachers fully excavated the subject knowledge points of the activity, and designed a variety of topics in the activity to let students think and learn, and the research trip became a disguised extracurricular training, and the students' interest in learning decreased significantly, deviating from the original intention and purpose of the combination of "learning" and "traveling" in the research trip, which greatly affected the effect of the activity [20-22]. In addition to this, the research activities themselves, such as safety problems, funding problems, mentor competence problems, and evaluation system problems, have also become the key constraints to the effective development of research travel. Therefore, from the practical level, it is crucial to study how to enhance the effectiveness of study tours [23-24].

In order to accurately assess the effect of ecological education in national park study activities, this paper establishes a Bayesian network and assesses the effect of ecological education by constructing an assessment model based on Bayesian inference. In order to know the assessment accuracy of the Bayesian inference assessment model constructed in this paper, it is compared with other assessment models, and the assessment performance of the model is judged by comparing the absolute error between the assessment value and the real value. The assessment index system is constructed based on the effect of research and study activities and ecological education, and the weights of the indexes are calculated. The assessment results of the ecological education effect are obtained by utilizing Bayesian backward reasoning and forward reasoning diagnosis. Finally, the probability that each assessment indicator is in various evaluation states is obtained by Monte Carlo simulation method.

2. Construction of a model for assessing the effectiveness of ecological education based on Bayesian inference

2.1. Basic Concepts of Bayesian Networks

Bayesian networks are derived from Bayes' theorem [25], which was proposed by Bayes, an English mathematician in the eighteenth century, and is mainly used as a method to represent the relationship between two conditional probabilities. Bayes' theorem combines human's a priori cognition of things and nascent evidence skillfully, and projects the development and change of things according to the change of evidence. The expression of Bayes' theorem is shown below:

$$P(A \mid B)=\frac{P(AB)}{P(B)} \tag{1}$$

In addition to the above expression, another very common expression is:

$$P(AB)=P(A \mid B)P(B) \tag{2}$$

The same reasoning can be obtained:

$$P(BA)=P(AB)=P(B \mid A)P(A) \tag{3}$$

After derivation the Bayesian formula can be obtained as the following equation:

$$P(B \mid A)=\frac{P(A \mid B)P(B)}{P(A)} \tag{4}$$

In equations (1), (2), (3) and (4), $P(A)$ is the probability of event A occurring, $P(B)$ is the probability of event B occurring, and the probability of event A occurring conditional on event B occurring is $P(A \mid B)$. Similarly, the probability of event B occurring conditional on event A occurring is $P(B \mid A)$.

Bayes' theorem consists of several conventions, as follows:

1) Prior Probability. A priori probability is the probability of occurrence of each event based on subjective experience, objective knowledge, historical information, etc. [26]. A priori probability is a description of the occurrence of things before the experiment, and is not confirmed by the experiment, but only an estimated probability. Based on varying methods of acquisition, a priori probability can be categorized into subjective a priori probability and objective a priori probability. The former pertains to probability derived from subjective experience, whereas the latter pertains to probability derived from historical information that is not mediated by human subjective consciousness.

2) Conditional probability. Conditional probability is the probability or likelihood that an event will occur under the condition that other events occur. For example, $P(A \mid B)$ in equation (1) is the conditional probability, which is the probability that event A occurs under the condition that event B occurs.

3) Joint probability. Joint probability refers to the probability of any two events occurring at the same time, formula (3) in $P(AB)$ and $P(BA)$ are joint probability, are the probability of event A and event B occurring at the same time.

4) Full probability formula. Full probability formula mainly refers to the impact of event A occurs all events $B_1, B_2 \ldots B_n$ all happen, the probability of event A occurs, the formula is as follows:

$$P(A) = \sum_{i=1}^{n} P(B_i) P(A \mid B_i) \tag{5}$$

The full probability formula needs to ensure that $B_1, B_2 \ldots B_n$ constitutes a complete set of events and all have positive probabilities.

5) A posteriori probability. The a posteriori probability refers to the probability estimate that is more in line with the actual situation by correcting the a priori probability after obtaining new evidence [27]. The a posteriori probability is inseparably linked to the a priori probability, and the calculation of the a posteriori probability should be based on the a priori probability.

Bayesian networks, also known as belief networks, or directed acyclic graph models, are probabilistic graphical models. A Bayesian network is an uncertainty handling model that simulates causality in human reasoning, and its network topology is a directed acyclic graph.

Individual nodes in the directed acyclic graph of a Bayesian network represent random variables $x_1, x_2 \ldots x_n$, which can be observable variables, or hidden variables, unknown parameters, etc. Two variables or propositions that are considered to be causally or non-conditionally independent are generally connected by arrows. If two nodes are connected by a single arrow, the node where one of the arrows starts is the “cause” and the node where the arrow ends is the “effect”, and a conditional probability value will therefore appear between the two nodes.

2.2. Steps in building a Bayesian network

Bayesian network can simulate the human cognitive thinking reasoning mode, is a set of conditional probability functions in the form of directed acyclic graphs to represent uncertain causal inference model, mainly used to describe the conditional dependence between random variables, for any random variables, the joint probability can be derived by multiplying their respective local conditional probability distributions as in equation (6):

$$P(x_1, \ldots, x_k) = P(x_k \mid x_1, \ldots, x_{k-1}) \ldots P(x_2 \mid x_1) P(x_1) \tag{6}$$

In general, Bayesian networks are constructed in the following three ways:

1) Experts identify the variable nodes of the Bayesian network and employ their expertise to construct the network's structure, while also specifying the parameter distributions within the network.This approach entirely relies on expert knowledge, which inherently involves human subjectivity and may consequently result in significant deviations in assessing the quality of the network and the outcomes of battlefield practice.

2) The structure and parameters of the Bayesian correlation posture assessment network are obtained through learning by the experts who determine the Bayesian network variable nodes and are trained with a large amount of data. This kind of Bayesian network obtained through learning is highly practical.

3) The experts determine the variable nodes of the Bayesian network, utilize the expert knowledge to establish the structure of the Bayesian network, and learn from a large amount of data to obtain the parameters of the assessment network. This way is suitable to be applied to the situation where the relationship between assessment indicators and information nodes is more obvious.

2.3. Parameter Learning and Bayesian Inference for Bayesian Networks

2.3.1. Parameter learning in Bayesian networks:

1) Maximum Likelihood Estimation. The maximum likelihood estimation method is based on classical statistical analysis ideas, based on the likelihood of the samples and parameters to judge the degree of fit of the data and structure [28]. Commonly used is the log-likelihood function, let the data set D consists of samples $(D_1, D_2, \ldots, D_N)$, then there are:

$$Ll(\theta \mid D, Sr) = \ln pl(D \mid \theta, Sr) \tag{7}$$

If D is fixed and θ is allowed to vary over its domain of definition, then $L(\theta \mid D, S)$ is a function of θ and is called the likelihood function of θ. The maximum likelihood estimate of parameter θ chooses parameter θ^* to maximize the likelihood function $L(\theta \mid D, S)$. Based on the assumption that the samples are independently and identically distributed and the structural features of the Bayesian network, there are:

$$\begin{aligned} L(\theta \mid D, S) &= \ln P(D \mid \theta, S) = \ln \prod_{l=1}^{m} P(D_l \mid \theta, S) \\ &= \ln \prod_{l=1}^{m} \prod_{i=1}^{n} P(x_i(l) \mid \Pi_{x_i}, \theta_i) = \ln \prod_{i=1}^{n} \prod_{j=1}^{q_i} \prod_{k=1}^{r_i} (\theta_{ijk})^{N_{ik}} \end{aligned} \tag{8}$$

where, m is the sample size, n is the total number of variables, q_i is the number of parent nodes of variable i, r_i is the number of values taken by variable i, and N_{ijk} is the number of values taken by variable i in case of k th parent node. Then there are:

$$\theta^*_{ijk} = \frac{N_{ijk}}{N_{ij}}, i = 1, 2, \ldots, n, j = 1, 2, \ldots, q_i, k = 1, 2, \ldots, r_i \tag{9}$$

2) Bayesian statistics. The Bayesian assumption is that the uninformative uniform distribution is used as the prior distribution, then the probability that the parameters are taken to each value is equal. Later scholars proposed the principle of maximum entropy, which is the distribution of the uninformative prior distribution to take the parameter with the maximum entropy in the range of variation. It has been proved that the sufficiently necessary condition for the entropy to be maximum is that the parameters obey a uniform distribution. Therefore, the Bayesian assumption is consistent with the maximum entropy principle of information theory.

Assuming that the prior distribution $P(\theta \mid S)$ of parameter θ is a Dirichlet distribution, there are:

$$\begin{aligned} P(\theta_y \mid S, D) &= \frac{P(\theta_y \mid S) P(D \mid S, \theta_y)}{P(D)} \\ &= \frac{\Gamma(\alpha_y + n_y)}{\prod_k \Gamma(\alpha_{yk} + n_{yk})} \prod_k (\theta_{yk})^{\alpha_{yk} + n_{yk}} \\ &= Dir(\alpha_{ij1} + n_{ij1}, \alpha_{ij2} + n_{ij2}, \ldots, \alpha_{ijr_i} + n_{ijr_i}) \end{aligned} \tag{10}$$

where n_{ijk} denotes the number of samples in sample set D that satisfy condition: $X_i = x_{ik}, \prod x_i = \prod_{x,}^{i}$. At this point the maximum a posteriori estimate of parameter θ is:

$$\theta^*_{ijk} = \frac{\alpha_{ijk} + n_{ijk}}{\sum_k (\alpha_{ijk} + n_{ijk})} = \frac{\alpha_{ijk} + n_{ijk}}{\alpha_{ij} + n_{ij}}, i = 1, \ldots, n, j = 1, \ldots, q_i, k = 1, \ldots, r_i \tag{11}$$

If the prior distribution is a common distribution, then the posterior information is used as the prior distribution for a new round of computation, which synthesizes the Bayesian structure with the sample information and makes full use of the relationship between the structure and the data.

However, for the rationality and accuracy of the prior distribution, the Bayesian method has no complete and exact theory that can prove.

2.3.2. Bayesian reasoning. Bayesian inference is also one of the first problems to be solved in Bayesian networks dealing with uncertainty [29]. Its main idea is to utilize the Bayesian network structure and conditional probability table to calculate the probability of the desired node taking values based on known conditions and inference algorithms. Bayesian inference algorithms are classified into two types: approximate inference algorithms and exact inference algorithms, both of which belong to the category of NP-complete problems. Among them, exact inference can be employed to effectively tackle numerous real-world problems.The more commonly used exact reasoning algorithms are SPI algorithm, Polytree algorithm, graph approximation algorithm and Junction tree algorithm.

The purpose of Bayesian inference is to obtain the joint distribution of variables through the network structure and the transitivity of known evidence. There are three main types of inference included in Bayesian network inference:

1) Predictive reasoning. From cause to conclusion, also called top-down reasoning that is, there is a direct causal relationship between two connected nodes. Then Bayesian network reasoning can be used to calculate the probability of the result occurring under the premise of that cause.

2) Diagnostic reasoning. From conclusion to cause, also called bottom-up reasoning. That is, when the result is known, the reason for the occurrence of that result is inferred. This reasoning is commonly used in pathological diagnosis and error diagnosis systems.

3) Supporting reasoning. Analyzing between different causes of the same result to derive the degree of interaction between the causes.

According to Bayes' theorem, inference can be made:

$$P(H=h \mid X=x)=\frac{P(H=h)P(X=x \mid H=h)}{P(X=x)} \tag{12}$$

where $H=h$ is the decision variable and $X=x$ is the condition variable.

2.4. Assessment methodology model

A Bayesian network contains a directed acyclic graph structure and a probability table for each node in the network. Each node represents a random variable or hypothesis, and each directed connection represents a relationship between two nodes, resulting in a parent-child relationship. Each node in a discrete Bayesian network has a finite set of possible values and only one of its possible values can be used at any given time. All child nodes, i.e., nodes with a parent, have a conditional probability table that models the combined influence of their parent, while each node without a parent has a prior probability table that describes their prior knowledge.

Essentially, a Bayesian network represents the probability distribution on the set $U=(A_1,A_2,A_3,A_4,\ldots,A_n)$ of variables in the network. The joint probability distribution $P(U)$ of the Bayesian network is $P(U)=P(A_1,A_2,\ldots,A_n)$, which can be decomposed here by using the product rule from Bayes' theorem as follows: $P(U)=\prod P(A_i \mid pa(A_i))$, where $pa(A_i)$ is the parent set of A_i, and the product rule must also be guaranteed to be conditionally independent. The probability of the target variable X is estimated algorithmically by the evidence at the given node A_i.

2.5. Model quantification

Model quantization is the process of parameterizing the conditional and prior probability tables of each node in a Bayesian network model. The links between each parent node and its children are numerically graded, and the parent-child links indicate the relationship between the parent and its children and the influence of the parent on the children. The data for Bayesian network calibration is obtained from the analysis of the links by first converting the grades into link weight percentages and then deriving the percentage probability values of the child node conditional probability tables from these link weights.

There may exist various types of probabilistic interactions between parent and child nodes, including union, compensation, separation, and inhibition.The interactions between nodes in the evaluation model are not compensatory because a low level on one parent of a child node is not compensated by a corresponding high level on one or the other parent. Interactions between nodes are modeled as joints, where the high-level state of a child node requires relatively high levels on all of its parents.

3. Effectiveness evaluation analysis based on Bayesian inference

3.1. Evaluate performance analysis

In order to test the accuracy of the Bayesian inference assessment model in this paper, it is tested together with other assessment models (BP neural network, CNN convolutional neural network, DBO-ELM model) for assessment performance. Students of school Q were selected as the research subjects, and 15 of them (numbered 1~15) were randomly selected to test and collect the subjects' ecological education performance. The assessment models were used to predict the ecological education performance of the 15 subjects, and the assessment effectiveness of each assessment model was judged by the absolute error between the prediction results and the actual results. According to the assessment of the four different assessment models mentioned above, the results and absolute errors of different assessment models were obtained as shown in Table 1.

As can be seen from Table 1, the maximum absolute error of the Bayesian assessment model is 0.5 points, which is smaller than that of the BP neural network model (5.0), the CNN convolutional neural network model (4.0) and the DBO-ELM model (4.8). The mean absolute errors of the Bayesian inference assessment model, BP neural network, CNN convolutional neural network, and DBO-ELM assessment model are 0.26, 2.99, 2.42, and 2.45 points, respectively. The Bayesian inference assessment model in this paper has the smallest maximum and mean absolute error of assessment. It can be seen that the assessment performance of the ecological education effect assessment model based on Bayesian inference in this paper is optimal.

Table 1. Fitting results of different assessment models

Student number	Real value	Bayesian		BP		CNN		DBO-ELM	
		Assess value	Absolute error	Assess value	Absolute error	Assess value	Absolute error	Assess value	Absolute error
1	74.5	74.7	0.2	72.2	2.3	76.6	2.1	77.1	2.6
2	79.4	79.9	0.5	74.4	5.0	75.4	4.0	76.9	2.5
3	72.1	72.3	0.2	68.5	3.6	70.2	1.9	74.8	2.7
4	80.3	80.8	0.5	77.4	2.9	78.2	2.1	78.6	1.7
5	73.1	73.1	0.0	71.2	1.9	75.6	2.5	73.7	0.6
6	70.5	70.2	0.3	73.8	3.3	69.1	1.4	75.3	4.8
7	66.3	66.8	0.5	67.4	1.1	67.5	1.2	70.9	4.6
8	73.2	73.5	0.3	77.8	4.6	75.7	2.5	75.9	2.7

9	76.5	76.5	0.0	74.8	1.7	72.6	3.9	74.8	1.7
10	78.8	78.6	0.2	79.0	0.2	76.3	2.5	75.9	2.9

3.2. Analysis of assessment results

3.2.1. Construction of the assessment indicator system and empowerment. The author analyzes the national park study activities and ecological education, and develops an indicator system for evaluating the effect of ecological education in national park study activities as shown in Table 2. The author mainly considers 4 aspects: the principle of ecosystem, the impact of human intervention, ecological disasters, and the situation of ecological protection measures, and from the 4 general indicators are divided into a number of specific variable indicators, i.e. sub-indicators. If the impact of each variable is to be analyzed completely and finely, on the one hand, it will make the established Bayesian network relatively large, and on the other hand, it is extremely difficult to collect information on so many variables in the assessment process, so the main variable indicators are selected and analyzed as the variables of the Bayesian network.

The Bayesian network analysis software Netica was used for analysis, and the state of node variables needed to be discretized. According to the specific situation, the discretization technology was used to deal with it, and the good state of the ecological education effect was defined as "GOOD", and the reverse effect was "BAD". The standard status of ecosystem principle, human intervention impact, ecological disaster, and ecological protection measures is "S1", and the non-standard status is "S2". Due to the relatively small amount of data, most variables consider only two states to reduce error.

The weight coefficients of the variables were corrected according to the Bayesian assessment model and the results of the calculations are shown in Table 3.

Table 2. Variables of Bayesian networks for ecological education effect

Variable type	Variable name	Symbol
Principle of ecosystem (A)	Terrestrial ecology	A1
	Marine ecology	A2
	Creature effect	A3
	Ecological operation rule	A4
	Ecological self-regulation	A5
Human intervention (B)	Greenhouse effect	B1
	Human pollution	B2
	Climate change	B3
	Overexploitation of natural resources	B4
Ecological disaster (C)	Meteorological disaster	C1
	Geologic hazard	C2
	Hydrological hazard	C3
	Biodiversity reduction	C4
	Degradation of forests and grasslands	C5
	Land degradation and desertification	C6
Ecological protection (D)	Nature reserve construction	D1
	Environmental protection legal construction	D2
	Environmental organization construction	D3
	Pollution control and reduction	D4
	Ecological development of natural resources	D5

Table 3. Adjusted results of weight coefficient by Bayesian assessment model

Batch	A1	A2	A3	A4	A5	B1	B1	B3	B4	C1
1	0.022	0.047	0.062	0.037	0.046	0.064	0.048	0.063	0.061	0.054
2	0.025	0.042	0.052	0.041	0.045	0.068	0.045	0.062	0.062	0.052
3	0.027	0.041	0.051	0.042	0.043	0.071	0.043	0.059	0.064	0.051
4	0.028	0.039	0.048	0.044	0.041	0.073	0.042	0.056	0.066	0.048
5	0.032	0.038	0.045	0.045	0.038	0.075	0.039	0.054	0.067	0.046
6	0.033	0.037	0.042	0.047	0.036	0.076	0.038	0.053	0.069	0.044
7	0.035	0.035	0.039	0.049	0.034	0.078	0.036	0.051	0.071	0.042
8	0.036	0.034	0.038	0.051	0.033	0.079	0.035	0.049	0.073	0.041
9	0.037	0.033	0.036	0.053	0.031	0.081	0.033	0.048	0.074	0.039
10	0.039	0.032	0.035	0.055	0.028	0.083	0.031	0.046	0.075	0.038
11	0.037	0.031	0.034	0.057	0.027	0.084	0.028	0.045	0.077	0.036
12	0.036	0.029	0.032	0.058	0.026	0.085	0.027	0.043	0.079	0.035
13	0.034	0.027	0.031	0.062	0.025	0.088	0.025	0.042	0.083	0.033
14	0.033	0.026	0.029	0.066	0.023	0.091	0.024	0.038	0.082	0.032
15	0.031	0.025	0.028	0.067	0.022	0.092	0.022	0.039	0.081	0.031
Batch	C2	C3	C4	C5	C6	D1	D2	D3	D4	D5
1	0.049	0.021	0.048	0.034	0.038	0.072	0.086	0.041	0.062	0.045
2	0.046	0.026	0.046	0.038	0.042	0.074	0.082	0.045	0.064	0.043
3	0.043	0.029	0.044	0.041	0.044	0.076	0.078	0.046	0.066	0.041
4	0.041	0.032	0.043	0.044	0.047	0.078	0.076	0.048	0.068	0.038
5	0.039	0.034	0.042	0.046	0.049	0.079	0.074	0.051	0.072	0.035
6	0.037	0.036	0.041	0.048	0.051	0.082	0.071	0.053	0.073	0.033
7	0.034	0.038	0.039	0.051	0.054	0.085	0.068	0.055	0.075	0.031
8	0.033	0.039	0.037	0.053	0.055	0.087	0.065	0.056	0.077	0.029
9	0.031	0.041	0.035	0.055	0.057	0.088	0.066	0.057	0.078	0.027
10	0.029	0.044	0.034	0.056	0.058	0.089	0.063	0.059	0.081	0.025
11	0.027	0.046	0.033	0.057	0.059	0.092	0.062	0.061	0.083	0.024
12	0.026	0.047	0.031	0.059	0.062	0.094	0.061	0.063	0.084	0.023
13	0.024	0.048	0.029	0.062	0.063	0.095	0.058	0.064	0.085	0.022
14	0.023	0.051	0.027	0.063	0.065	0.096	0.057	0.065	0.087	0.022
15	0.022	0.053	0.026	0.065	0.067	0.097	0.055	0.067	0.088	0.022

3.2.2. Impact assessment and decision support. Backward inference diagnosis was performed using Bayesian network and the diagnostic results are shown in Table 4. The levels that should be guaranteed to be achieved in ecological education in the four aspects of the model: ecosystem principles, human intervention impacts, ecological disasters and ecological protection measures can be obtained as 75.6, 64.8, 67.9 and 69.4, respectively. Comparison of these sets of data, observed that the initial state value of the ecosystem principle "S1" and the expected value of the state of a large difference, at this time, we can know the weak links and short boards, should be targeted to strengthen the construction.

Table 4. Diagnosis of Bayesian network

Variable	S1 posterior probability	S2 posterior probability	Variable	S1 posterior probability	S2 posterior probability
Education effect	100%	0	Education effect	100%	0
A	75.6%	24.4%	C1	53.6%	46.4%
A1	80.4%	19.6%	C2	53.5%	46.5%
A2	54.7%	45.3%	C3	62.7%	37.3%
A3	49.5%	50.5%	C4	66.3%	33.7%
A4	51.6%	48.4%	C5	58.4%	41.6%
A5	48.7%	51.3%	C6	60.9%	39.1%
B	64.8%	35.2%	D	69.4%	30.6%
B1	42.5%	57.5%	D1	62.3%	37.7%
B2	65.4%	34.6%	D2	59.4%	40.6%
B3	48.5%	51.5%	D3	61.7%	38.3%
B4	67.1%	32.9%	D4	64.3%	35.7%
C	67.9%	32.1%	D5	65.5%	34.5%

Then forward inference is carried out through Bayesian network to get the change of forward inference of sub-indicators to total indicators as shown in Table 5. As can be seen from Table 5, ecological operation rule A4 has the most prominent influence on ecosystem principle A (59.4→79.8) and ecological education effect (52.6→58.6), and similarly, climate change B3, biodiversity reduction C4 and pollution prevention and control D4 have the most prominent influence on anthropogenic intervention influence B (50.6→70.2), ecological disaster C (52.2→69.8) and ecological conservation measures D (56.4→78.3) and the effect of ecological education are more influential, implying that reinforcement from these links achieves the effect more quickly.

Table 5. Changes in forward inference of sub-indicators to total indicators

Sub-indicator		Teaching effect	A	Sub-indicator		Teaching effect	B
Variable	Set value	Posterior probability	Posterior probability	Variable	Set value	Posterior probability	Posterior probability
	S1	GOOD	S1		S1	GOOD	S1
-	-	52.6%	59.4%	-	-	52.6%	50.6%
A1	100%	54.1%	62.3%	B1	100%	50.3%	63.5%
A2	100%	53.6%	61.5%	B2	100%	51.6%	66.7%
A3	100%	51.4%	65.2%	B3	100%	55.8%	70.2%
A4	100%	58.6%	79.8%	B4	100%	52.4%	67.9%
A5	100%	52.6%	60.2%	-	-	-	-
Sub-indicator		Teaching effect	C	Sub-indicator		Teaching effect	D
Variable	Set value	Posterior probability	Posterior probability	Variable	Set value	Posterior probability	Posterior probability
	S1	GOOD	S1		S1	GOOD	S1
-	-	52.6%	52.2%	-	-	52.6%	56.4%
C1	100%	53.4%	66.5%	D1	100%	51.4%	68.4%
C2	100%	55.2%	64.8%	D2	100%	52.8%	59.4%
C3	100%	52.6%	65.2%	D3	100%	53.4%	65.7%
C4	100%	57.4%	69.8%	D4	100%	56.9%	78.3%
C5	100%	51.9%	63.8%	D5	100%	53.8%	64.5%
C6	100%	54.6%	64.2%	-	-	-	-

3.2.3. Results of Educational Effectiveness Assessment. Student ecological education information is gathered through examination records and other methods, and these data undergo preprocessing to eliminate outliers. Based on this preprocessed training data, each assessment element is scored according to the assessment guidelines outlined in Table 2, ultimately yielding ecological education assessment scores.At the same time, the item scores of the corresponding assessment indicators are determined according to the weights of each assessment element, and finally, the assessment scores are converted into the probability of each assessment indicator being in various evaluation states through Monte Carlo simulation method as shown in Table 6.

As shown in Table 6, the overall score of the ecological education effect measured in this study is 84.1, and the scores of ecosystem principle, human intervention impact, ecological disaster, and ecological protection measures are 83.8, 85.2, 83.0, and 84.2, respectively, with 81.4%, 85.8%, 76.3%, and 100% probability of achieving a good and above effect, respectively.

Table 6. Ecological education performance

Indicator	Probability/%	State	Score	Weight	Variable	Score
Principle of ecosystem	12.7	Excellent	83.8	0.179	A1	83.2
	68.7	Good		0.145	A2	80.1
	18.6	Pass		0.162	A3	76.4
	0	Not pass		0.387	A4	93.8
	-	-		0.127	A5	68.2
Human intervention	20.2	Excellent	85.2	0.393	B1	81.9
	65.6	Good		0.094	B2	70.7
	14.2	Pass		0.167	B3	91.7
	0	Not pass		0.346	B4	89.8
Ecological disaster	16.7	Excellent	83.0	0.117	C1	80.9
	59.6	Good		0.083	C2	94.8
	23.7	Pass		0.201	C3	82.9
	0	Not pass		0.099	C4	69.0
	-	-		0.246	C5	88.0
	-	-		0.254	C6	80.9
Ecological protection	25.6	Excellent	84.2	0.295	D1	92.1
	74.4	Good		0.167	D2	92.8
	0	Pass		0.204	D3	88.3
	0	Not pass		0.267	D4	69.0
	-	-		0.067	D5	75.8

4. Conclusion

The article employs Bayesian network methodology to evaluate the impact of ecological education within national park study activities and constructs an effectiveness assessment model grounded in Bayesian inference.The assessment performance of the Bayesian assessment model is examined, and it is applied to practice to analyze its assessment results.

The mean absolute error of the Bayesian assessment model is 0.26 points, which is smaller than that of the BP neural network model (2.99), CNN convolutional neural network model (2.42) and DBO-ELM model (2.45). The Bayesian assessment model constructed in this paper has the highest assessment accuracy.

The model's ecosystem principle, human intervention impact, ecological disaster and ecological protection measures should be guaranteed to reach the level of 75.6, 64.8, 67.9 and 69.4, respectively. ecological operation rules, climate change, biodiversity reduction and pollution prevention and control have a significant impact on the ecosystem principle (59.4→79.8), human intervention impact (50.6→70.2), ecological disaster (52.2→69.8) and ecological protection measures (56.4→78.3) and the effect of ecological education had the greatest influence. The overall score for the effectiveness of ecological education was 84.1, with 81.4%, 85.8%, 76.3%, and 100% probability of achieving a good or above effect in ecosystem principles, human intervention impacts, ecological disasters, and ecological protection measures, respectively.

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