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Research on Intelligent Early Warning and Closed-Loop Nursing Intervention Model of Pet Subclinical Health Risk

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Abstract

This study addresses the challenge of detecting pet subclinical health risks, where physiological abnormalities occur without obvious clinical symptoms, leading to delayed intervention and high subsequent medical costs. Existing wearable pet monitoring devices mostly rely on single-threshold alarms and lack multi-indicator comprehensive risk evaluation, while few studies incorporate implementation compliance and response delay into health-economic assessment. This paper constructs an intelligent early-warning and closed-loop nursing intervention model for pet subclinical health risks. An entropy-weight method is adopted to fuse 12 physiological and behavioral monitoring indicators to calculate individual subclinical risk scores. A discrete-time Markov chain model simulates monthly state transitions among health, subclinical, and clinical conditions. Three intervention scenarios (traditional manual observation, open-loop intelligent monitoring, closed-loop intelligent monitoring) are established, and cost-effectiveness analysis is performed using quality-adjusted health-life-month outcomes. Simulation results show that the risk-scoring model achieves an AUC of 0.8395. Compared with traditional observation, the closed-loop intervention reduces the three-year cumulative clinical incidence by 32.3%. The incremental cost-effectiveness ratio of the closed-loop mode is 1424 yuan/QAHLY, which is economically acceptable under a conservative willingness-to-pay threshold. Findings indicate that improving implementation compliance and shortening response delay deliver greater health gains than merely boosting detection performance. This model provides technical and economic references for pet-wearable product design, insurance cooperation, and popularization of early pet-health intervention.

Keywords: Pet Subclinical Health Risk; Entropy-Weight Method; Markov Model; Closed-Loop Nursing Intervention; Cost-Effectiveness Analysis; Intelligent Pet Monitoring

1. Introduction

1.1. Research Background

In 2024, China's urban dog and cat consumer market reached 345.3 billion yuan, and the number of pets will be about 120 million. Among them, the market size of intelligent pet products will reach 10.2 billion yuan. The annual growth rate of health monitoring products is close to 180%, but the penetration rate is still less than 20%. The market size is expanding, but pet care has been stuck on two issues, which is in contrast to the market growth rate.

The first is that the early disease is found late and the cost of treatment is high. Chronic kidney disease will have obvious clinical manifestations when about 67%-70% of renal function is lost. Marynissen et al. conducted a two-year follow-up study on 122 apparently healthy elderly dogs. At baseline, 12% of the elderly dogs had non-nitrogenous CKD, and 20% of the elderly dogs developed CKD two years later. The prevalence of CKD increases with age, being estimated at 20-50% in cats over 10 years of age. In a review by Grecu et al. (2025), it is estimated that the prevalence rate of cats over 15 years old can reach about 80%. After entering the clinical stage, the annual treatment and maintenance costs will reach thousands to tens of thousands of yuan.

The second problem is that the subclinical stage is difficult to detect. During this period, there was no obvious abnormality in the appearance and behavior of the animals, and there were only some slight changes in various physiological indicators. Cortisol increased slightly, exercise decreased slowly, and sleep structure was also different. These offsets are the most valuable information in the intervention window period, but the owner can not be found only by observation in daily life. Whether the window period can be grasped will directly affect the subsequent intervention costs and the final results of the animals.

The problem to be solved in this paper is also determined, that is, how to transform the weak signals from multiple sources obtained by continuous monitoring into reliable early warning information, and further into the actual implementation of nursing behavior.

1.2. Research Significance

There is no big problem in the number of indicators of existing pet wearable devices. There are three things that are really stuck.

First, the number of indicators is no longer a problem. What is really stuck is how these indicators synthesize a credible score. The sensitivity of physiological indicators and behavioral indicators to risk is different. Let the veterinarians score item by item based on experience, the weights given by different doctors can be much worse; simple equal weight addition, sensitive indicators will be submerged in more than a dozen dimensions. Li, Sun, and Du (2025) have encountered similar problems in the construction of China's pet market index. Their approach is to replace expert empowerment with entropy weight method. This article follows this idea, but the evaluation object has changed from the level of market development to the degree of deviation of individual pets.

Second, the device only gives a snapshot of the moment, and can not answer ' will the disease occur in a few months '. What the master really wants to ask is the probability, not the score at the moment. To answer the probability, there must be a model describing the evolution of the state over

time. In this paper, the discrete-time Markov queue model is used to complement this link: the monthly transfer between the three states of health, subclinical and clinical is written as a matrix, and then pushed forward month by month.

The third is the lack of economic evaluation. Technically, whether early warning is possible is another thing, and whether the early warning value is worth promoting is another thing. In this paper, the cost-effectiveness analysis method is used to judge the increase of quality-adjusted health life months caused by the cost of closed-loop intervention compared with traditional observation. The threshold is 10000 yuan/QAHLY. According to the Chinese Guidelines for Pharmacoeconomic Evaluation (2020), this result falls within the economically acceptable range ($1 \times GDP < ICER \leq 3 \times GDP$). In Section 7.5, the results of sensitivity analysis under three different thresholds are given.

After adding three questions, this paper continues to answer where and how much the closed-loop is better than the open-loop. It has direct guiding significance for the pricing of products, the cooperation of insurance and the way of promotion.

1.3. Research Status at Home and Abroad

Pet wearable devices abroad have PetPace collars that can monitor body temperature, pulse, respiration, activity, and sleep. Belda (2018) has done preliminary research on this; Sylvester.ai uses facial images to identify whether the cat is painful, which is not the same technique; Whistle is dominated by activity and positioning. Most of the products of domestic millet ecological chain, CATLINK and Hohmann are also focused on activity, positioning, and some physiological indicators. The general trend is from single activity to multi-parameter expansion. However, most products stop at the step of single-index threshold alarm, and the problem of " how to comprehensively evaluate multiple indicators " has been rarely studied. In terms of weighting methods, Delphi method, analytic hierarchy process (AHP), principal component analysis and entropy weight method are common tools. The entropy weight method developed from Shannon information entropy is widely used in multi-index evaluation (Shannon,1948, Guo & Qiu, 2002) .

In the course of disease modeling, Markov model can be used to model the process of chronic diseases. Briggs et al. presented the modeling process of Markov decision model in health economic evaluation. Drummond et al. and the "Chinese Pharmacoeconomic Evaluation Guide (2020 Edition) "both explained the calculation and judgment criteria of ICER. This method can be used for economic assessment of pet health, but due to the different sources of parameters, the data of the human cohort cannot be directly used on dogs and cats.

There are still some shortcomings in the current research. When most of the results are discussed around the question of ' can be measured accurately ' and ' how is the accuracy of the algorithm ', few people will put the three factors of detection ability, owner execution rate and response delay in a model to investigate, and no one uses ICER to evaluate whether pet health interventions are worthy of promotion and application. This article is supplemented in the above two places.

2.Related Theory and Technical Basis

2.1. Subclinical Status and Monitoring Index System

This paper divides the whole process of pet health into three categories. Healthy state (H): The physiological indexes are within the normal range of the individual, and there is no obvious deviation. Subclinical state (S): The appearance and behavior are basically normal, but the physiological indicators have begun to systematically shift slightly, which is the best time for intervention. State C: the state that the owner or veterinarian can perceive and take measures.

According to the business plan of the project team and related literature, in this study, 12 intelligent collars were selected to continuously collect data as monitoring indicators to form a set of monitoring indicators, as shown in Table 1.

However, the degree of continuous acquisition of these 12 items is different. Heart rate, respiratory rate, exercise and sleep have been independently verified in many studies; continuous blood glucose monitoring in dogs showed clinically acceptable accuracy; noninvasive continuous monitoring of cortisol is still in the initial exploration; blood oxygen and blood pressure are limited by hair signal weakening and accuracy, and it is impossible to talk about whether there is continuous monitoring capacity at the clinical level; the change of body weight is physically impossible to be directly measured by the collar, and the accuracy of the activity-to-energy conversion algorithm in dogs is limited.

In this paper, they are included in the indicator set as ' candidate monitoring dimensions ', not to say that each has developed to an equal level of maturity. This distinction will be encountered many times in each chapter.

Table 1. 12 monitoring indicators and their health implications

Serial Number	Index	The Meaning of Health	Atypical Direction	Acquisition Mode
1	Blood Sugar	Glucose metabolism, diabetes and insulin resistance markers	Ascension	Collar direct collection
2	Cortisol	Core stress hormones, long-term elevated prompt chronic stress	Ascension	Collar direct collection
3	Heart Rate	Cardiovascular load and pain response	Increase / decrease	Collar direct collection
4	Body Temperature	Inflammation, infection and metabolic abnormalities	Increase / Decrease	Collar direct collection
5	Respiratory Rate	Cardiopulmonary function and pain, respiratory diseases	Ascension	Collar direct collection
6	Skin Conductivity	Sympathetic nerve excitement, reflecting acute emotional stress	Ascension	Collar direct collection

Serial Number	Index	The Meaning of Health	Atypical Direction	Acquisition Mode
7	Arterial Oxygen	Blood oxygen saturation reflects circulatory and respiratory function	Reduction	Collar direct collection
8	Blood Pressure	Circulatory system load, kidney disease often associated with high blood pressure	Ascension	External input + interpolation
9	Metabolic Rate	Energy expenditure level, associated with thyroid, digestion and absorption	Increase / Decrease	External input + interpolation
10	Body Weight Change	Important signals of nutrition and chronic wasting diseases	Descent	External input + interpolation
11	Activity Amount	The direct embodiment of overall vitality and pain, depression	Descent	External input + interpolation
12	Sleep Quality	Sleep structure and recovery ability, stress can destroy sleep	Variation	External input + interpolation

According to data acquisition feasibility, the 12 monitoring indicators are divided into two categories. The first category can be continuously collected by the smart collar. The second category cannot be measured continuously by wearable collars, which requires periodic offline veterinary detection and manual entry. Continuous time-series data of these indicators are obtained by temporal interpolation, which inevitably introduces estimation error. Such indicators are treated as candidate monitoring dimensions rather than direct diagnostic evidence in subsequent modelling.

The basic values of various animals are far from each other, so the amount of exercise of large dogs and small dogs cannot be directly compared. Therefore, we can 't use absolute value to alarm, only to compare with the individual 's own previous basic level. Therefore, ' deviation degree ' will be used in Chapter 4.

2.2. Basic Principle of Entropy Weight Method

Entropy was originally derived from thermodynamics, and Shannon applied it to information theory to represent the magnitude of system uncertainty (Guo & Qiu, 2002).

Setting n evaluation objects and m evaluation indexes,the non-negative matrix $Z=(z_{ik})_{n\times m}$ is obtained after normalization. The entropy of the kth index is defined as:

$$e_k=-\frac{1}{\ln n}\sum_{i=1}^{n} p_{ik}\ln p_{ik} \qquad p_{ik}=\frac{z_{ik}}{\sum_{i=1}^{n} z_{ik}} \tag{1}$$

When $p_{ik}=$ is set to 0, $p_{ik}\ln p_{ik}=0$. Thus, the weight of the kth index is obtained

$$w_k=\frac{1-e_k}{\sum_{j=1}^{m}(1-e_j)}, \qquad k=1,2,\ldots,m \tag{2}$$

Here $1-e_k$ is called the difference coefficient, which reflects the relative importance of the index.

The advantage of the entropy weight method is that it is completely driven by data, and the subjective preferences of the evaluators cannot be plugged in. The disadvantage is also in the same place, it only sees the data scattered, not to see the index itself is clinically important or not. Therefore, after calculating the weight, we must combine the domain knowledge to test the results again.

2.3. Markov Chain and State Transition Model

Markov chain is one of the most commonly used tools for stochastic processes. Its main feature is memorylessness. The t + 1 state of the system is only related to the t state and has nothing to do with the previous state. Suppose that the state space is a discrete set, the row vector π (t) is used to represent the probability distribution of each state at time t, and the one-step transition probability matrix is P, then there is

$$\pi(t+1)=\pi(t)P, \qquad \sum_j P_{ij}=1 \tag{3}$$

Markov models are widely used to represent the movement between different health states over time; the method is to divide the disease into several mutually exclusive and complete health states, and divide the time into equal length time periods. In this paper, one month is taken as the time period, and the transition probability matrix is used to represent the transition between various states. By setting the initial queue distribution, and then calculating it forward step by step, the average stay time and cumulative incidence of each state can be obtained. The structure of this method is simple and clear, the meaning of the parameters is also very intuitive, and the sample size is not too high.

2.4. Cost-Effectiveness Analysis and ICER Criteria

The question answered by Cost-Effectiveness Analysis (CEA) is ' How much health benefits does the increased cost bring '. If the cost of control scheme A and scheme B to be evaluated is C_A,C_B and the effect is E_A,E_B respectively, the incremental cost-effectiveness ratio is

$$\mathbf{ICER}=\frac{\Delta C}{\Delta E}=\frac{C_B-C_A}{E_B-E_A} \tag{4}$$

The results are judged according to the criteria in Table 2. Where λ_0 is the willingness to pay threshold of the decision maker, which means the maximum amount that the decision maker is willing to pay for a unit of health output.

Take λ_0 = 10000 yuan/QAHLY as the benchmark threshold. It should be noted that the value is quite conservative. The Chinese Pharmacoeconomic Evaluation Guide (2020 Edition) ' recommends 1-3 times per capita GDP as the threshold. According to the per capita GDP of about 70-85 thousand yuan in recent years, the threshold of the guide falls in the order of 70-25 thousand yuan/QALY. This article takes 10000 yuan, only about 1/7 of the lower limit of the guide.

The purpose of this is to show whether the scheme can be established under the very conservative willingness to pay. Section 7.4 will also report the judgment results under the threshold of 1 and 3 times per capita GDP, so as to prevent the conclusion from relying on a single threshold. In addition, in Table 2, when the cost and effect decrease, the ICER is negative. At this time, the absolute value

is compared with the threshold, and the direction of the unequal sign is opposite to the positive quadrant.

Table 2. incremental cost-effectiveness criteria

Circumstance	ΔC	ΔE	Judgement Result
Strictly Dominant	<0	>0	Scheme B is more economical and better, directly adopted.
Need to Weigh	>0	>0	ICER $<\lambda_0$ is cost-effective; not recommended otherwise.
Need to Weigh	<0	<0	ICER $>\lambda_0$ accepts to save money in exchange for loss of effect.
Strict Dominated	>0	<0	Scheme B is more expensive and worse, and rejects directly.

3.The Overall Design of Pet Subclinical Health Warning and Closed-Loop Intervention System

3.1. Overall Architecture of the System

The system is built according to the four layers of perception layer, network layer, platform layer and application layer, and its structure is as follows.

The sensing layer refers to the collar itself, which is equipped with flexible physiological sensors, attitude sensors, voiceprint sensors, odor sensors, with GPS + Beidou positioning module. The network layer is Bluetooth 5.0 near-field synchronization, plus 4G/NB-IoT remote upload. The endurance time of the collar is about 15 days, and it has IPX7 waterproof grade. The platform layer is located in the cloud, which completes data cleaning, individual baseline establishment, early warning model inference and hierarchical decision-making, and connects with the HIS system of veterinary institutions through API.

3.2. Data Acquisition Index and Acquisition Frequency

This paper is divided into three layers according to different indicators. The high frequency layer includes data such as heart rate, respiration, activity and posture, which is collected once in about 1 minute. The intermediate frequency layer contains data such as body temperature and skin conductivity, which is collected every few minutes. The blood glucose, cortisol, blood oxygen, blood pressure and other data in the low frequency layer are determined according to the actual performance of the sensor, and are labeled as ' trend reference ' on the APP side, not as ' diagnostic basis '.

It should be noted that, consistent with the feasibility classification in Section 2.1, the system architecture does not assume that all 12 indicators can be integrated in the same way: heart rate, respiratory rate, activity, sleep, body temperature and skin conductivity are directly and

continuously collected by the wearable collar, and blood glucose is continuously collected with clinically acceptable accuracy, whereas cortisol must be obtained through periodic offline veterinary testing (blood or saliva sampling) with manual entry and interpolation, blood pressure and blood oxygen are collected by the collar but used only as 'trend reference' due to limited accuracy, and body-weight change and metabolic rate rely on external weighing and indirect estimation. The platform layer processes the two classes of data through separate channels and never uses externally estimated indicators as direct diagnostic evidence.

The " full indicator sampling per minute " mentioned in the business plan is a product promotion term, not to say that these 12 items can be done. Table 3 gives the upper limit of the design parameters of the platform layer. The measurement error ± 3% is the expected target value in the case of static prototype, and the error will be greater in the case of free movement of animals.

The device can capture the change of cortisol 0.05 mg/L level, the change of body weight 5 g level and the change of limb 0.5 ° angle, so it provides a hardware basis for the capture of weak signal in subclinical stage. However, hardware parameters do not represent the accuracy that can be used for clinical continuous monitoring. When modeling, the detection rate is used as a scenario parameter, and it is not directly calculated by these hardware indicators. The reason is that:

Table 3. key parameters of data acquisition

Item	Index Parameters
Number of Monitoring Indicators	12 items (physiology + behavior)
Sampling Frequency	1 time/min
Measurement Error	± 3%
Location Mode	GPS + Beidou, accuracy ≤ 5 m
Near Field Communication	Bluetooth 5.0
Endurance/Waterproof	about 15 days/IPX7
Number of Device Bindings	≤ 10 units
Data Synchronization Delay	≤ 2s

3.3. Classified Early Warning Function Design

These are the three things that the platform layer needs to do after obtaining real-time data.

The first thing is to establish an individual baseline. After wearing a pet for a certain number of days, the data distribution of each index in the stable period was selected as the health basis of the pet. After that, all warnings are based on the standard of ' deviation from the individual 's basic value ', avoiding individual differences caused by factors such as variety, body type, and age.

The second step is to calculate the scores and then classify them. According to the risk score R of the fourth chapter model one synthesis, it is divided into three grades, low, medium and high.

Low risk only shows trend on APP; risk will push nursing advice, such as changing the way of feeding, drinking more water, paying attention to defecation; high-risk will be accompanied by text messages and voice calls, and automatically generate a case summary that can be directly sent to the cooperative hospital.

The third thing is to ask the veterinarian to participate. High-risk cases will be pushed to the pet hospital bound by the pet owner using the API within 1 minute, and then reviewed by the veterinarian to determine whether they need to go to the hospital. So far, a closed loop of information between equipment, platform, veterinarian and pet owner has been formed.

3.4. Closed-Loop Intervention Link

The main content of the closed loop is to have an ' execution ' link after the early warning. Two execution paths are designed in this system.

The way of human operation. After receiving the grading suggestion on the APP, the pet owners perform operations manually, adds water, feeds, cleans the cat sand, and adjusts the indoor temperature. The degree of ability to do is affected by the energy, cognition and trust of the pet owner, which is the implementation compliance rate ρ mentioned in this paper. For automatic operation: Without the intermediate link of people, it is completed by equipment linkage. The system has opened up ecological equipment such as CATLINK, Xiaomi Youpin, Holman, etc. and can automatically trigger functions such as water dispenser replenishment, feeder replenishment, air conditioning temperature adjustment, etc. The linkage success rate is greater than or equal to 99%, and the response delay is less than or equal to 2 seconds. The significance of this path is to bring ρ closer to 1.0, that is, by human consciousness. In the fifth chapter and the sixth chapter, the reason for the gap between mode C and mode B is there.

The system also has an emotion-demand translation module, which converts snoring, hiding, loss of appetite and other behaviors and physiological signals into operational demand categories such as pain, anxiety, thirst, environmental discomfort, etc. to help the owner figure out what the animal really needs. According to the survey data of the business plan, 83% of pet owners admit that they cannot accurately judge the needs of pets, and 19% of them miss the optimal intervention window.

This module belongs to the category of product function design, and does not model the algorithm, but only reflects its improvement effect on the detection rate δ through parameter setting.

4.Multi-Index Weighted Health Risk Scoring Model

4.1. Calculation and Normalization of Individual Deviation

The first section of the second chapter has mentioned that the values of the 12 detection indicators cannot directly compare different individuals, and there is no uniform medical standard value. Therefore, the model input should not be the absolute value of the animal, but the degree of deviation of the animal relative to its own health. After determining this point, there are two problems that have not been solved. One is how much deviation is an anomaly, and the other is how to determine the importance of each indicator. These two are carried out separately, first to

determine the standard ruler, and then to determine the weight.

Suppose that the i th pet (i=1,…,n) is on the kth index (k=1,…,m, m=12), and the signed deviation in an observation window is Δ_{ik}, define

$$\Delta_{ik}=v_{ik}-b_{ik} \tag{5}$$

Among them, the observed mean is denoted as v_{ik}, while b_{ik} represents the health baseline mean of the animal, which is determined by the stable data collected at the initial stage of wearing.The abnormality of most indicators may be manifested as an increase, such as cortisol and blood glucose, or a decrease, such as activity and blood oxygen. Both directions mean that the risk rises, so the absolute value is taken uniformly to construct a positive deviation range. Doing so will lose the direction information, but there is no way, can only see the absolute value when it is not clear :

$$x_{ik}=|\Delta_{ik}| \tag{6}$$

The greater the x_{ik}, the farther the animal deviates from its baseline in the kth indicator, the higher the risk. In order to eliminate the dimensional difference, it is mapped to [0,1] by range normalization:

$$z_{ik}=\frac{x_{ik}-\min_i x_{ik}}{\max_i x_{ik}-\min_i x_{ik}} \tag{7}$$

The normalized matrix Z=(z_{ik}) is the input of the entropy weight method.

4.2. Weight Solution Based on Entropy Weight Method

According to the principle of entropy weight method in Section 2.2, the proportion of the kth index is first calculated for the normalized matrix Z.

$$p_{ik}=\frac{z_{ik}}{\sum_{i=1}^{n} z_{ik}} \tag{8}$$

Thus, the entropy and weight are calculated.

$$e_k=-\frac{1}{\ln n}\sum_{i=1}^{n} p_{ik}\ln p_{ik}, \qquad w_k=\frac{1-e_k}{\sum_{j=1}^{m}(1-e_j)} \tag{9}$$

This weight is determined by the degree of data dispersion of the index: the more dispersed the distribution of a certain index in the sample, that is, the greater the deviation difference between different individuals, the smaller the entropy value and the greater the weight. Intuitively also makes sense. The indicators that can distinguish individuals have a large amount of information. By the way, the weight calculated by the entropy weight adds up to 1, which is convenient to use.

The entropy weight method obtains the information weight in the statistical sense, which cannot directly represent the clinical importance. Therefore, after calculating the actual weight in the second section of Chapter 7, we should refer to the medical significance of Table 1 to test whether the results are reasonable.

4.3. Risk Score and Classification

The sub-clinical health risk score of the ith pet was synthesized by the following formula :

$$R_i = \sum_{k=1}^{m} w_k \ z_{ik}, \qquad 0 \le R_i \le 1 \tag{10}$$

The greater the R_i, the greater the current deviation of the pet from normal, and the greater the possibility of existence in the subclinical state. After calculation, a threshold should be set. If the threshold is not set well, the previous work is done in vain. In this paper, two methods of threshold selection are studied.

One is the optimal principle of Youden index: traverse all possible candidate thresholds and select the one that makes the ' sensitivity + specificity-1 ' reach the maximum as the comprehensive judgment cut-off point. It is suitable for general screening occasions that have certain requirements for missed diagnosis rate and false alarm rate.

The second is the principle of high sensitivity screening. When the sensitivity is not less than 0.90, the cutoff value with the highest specificity is taken. This article is more inclined to the latter. The reason is that the cost of missed diagnosis in the subclinical stage is the loss of the opportunity to intervene, and the cost of misreporting is only one more examination. The two are not on the same order of magnitude. This principle can meet the needs of pet owners and veterinarians.

The risk level is divided by the method of three equal samples, and all the scores are arranged from small to large. The first 1/3 is low risk, the middle 1/3 is medium risk, and the last 1/3 is high risk, which correspond to the three-level early warning strategy in the third section of the third chapter. One of the benefits of this division is that the proportion of samples in each level is equal, and the push resources are better controlled. The specific entry point is derived from the results of the second section of Chapter 7. So why not use the clustering method? This article has also had such an idea. The third quartile is very simple, push volume can also be well controlled, so choose it.

5.Subclinical State Transition Markov Model

5.1. State Partition and Basic Assumptions

Model one gives a risk snapshot at a certain time point. But the other thing that owners and veterinarians are concerned about is: at the sub-clinical stage, how likely will it be to progress to clinical disease in the next three years? How much probability can intervention be reduced? In order to get the answer, it is necessary to establish a model that describes the state of the system over time.

Using the discrete-time Markov queue model introduced in Section 2.3, we treat the health process of each pet as three mutually exclusive, complete states:

State H (health): All indicators are within the normal range of the individual;

Status S (subclinical): The indicators have begun to deviate systematically, but there are no obvious symptoms;

State C (clinical): a state that has been diagnosed and requires treatment. This article considers it to be an absorbing state.

The model is based on the following assumptions:

H1: No sequelae. The state of next month is only related to the state of this month, and has nothing to do with the state of the previous month. This is the Markov property itself, there is nothing to discuss.

H2: Time consistency and integrity requirements. The transition probability was the same throughout the follow-up period.

H3: The Markov state-transition cycle is one month. Nursing intervention actions can be executed on a weekly basis, but health-state transition evaluation is performed monthly, and each pet can undergo at most one health-state transition within one month.

H4: The clinical state is an absorption state. Once it enters C, it stops there and no longer returns S or H.

In practice, clinical pets may recover after veterinary treatment. This study focuses on evaluating the early warning effect of preventing subclinical progression to clinical status, instead of modelling the treatment and recovery process after clinical onset. Therefore, the recovery branch from the clinical state is simplified in the current model. This limitation will be discussed in the discussion section, and a semi-Markov model can be adopted in future research to add a recoverable clinical state.

H5: Intervention acts on the transition probability. Closed-loop intervention does not change the state that has occurred, but delays the onset by reducing the monthly transition probability from S to C. This is the key to the whole model. Section 5.3 is devoted to it.

Among these five, H2 and H4 are two strong hypotheses. In the real course of disease, aging will increase the transition probability of H to S with age; state C may also have regression or death branches due to different diseases. This article retains these two in order to control the model within the analytical range. In Section 8.2, ' age-dependent transition probability ' and ' semi-Markov model ' are listed as improvement directions.

5.2. State Transition Matrix Without Intervention

Monthly transition probability: p_{HS} is the probability of health to subclinical, p_{SH} is the probability of subclinical recovery to health, $p_{SC}^{(0)}$ is the probability of subclinical to clinical without effective intervention. Then the transition probability matrix on the state set $\{H,S,C\}$ is

$$P=\begin{bmatrix} 1-p_{HS} & p_{HS} & 0 \\ p_{SH} & 1-p_{SH}-p_{SC} & p_{SC} \\ 0 & 0 & 1 \end{bmatrix} \tag{11}$$

Combined with the clinical experience of veterinarians, as well as the epidemiological parameters in the business plan, this paper takes the reference value.

$$p_{HS}=0.020, \quad p_{SH}=0.050, \quad p_{SC}^{(0)}=0.100 \tag{12}$$

These numbers mean that healthy pets have a probability of about 2% per month to enter subclinical, which corresponds to the accumulation of aging and chronic stress; pets in the

subclinical state have a 5% probability of spontaneous recovery or improvement by general care every month. If no effective intervention is taken, there is a 10% probability of progression to clinical disease. Three numbers are not big. Push up to 36 months, the difference came out. These numbers were asked by the veterinarian and also referred to the epidemiological parameters in the business plan. Frankly speaking, the subjective component is not small. To make the basis of these parameters transparent, the sources, rationale and plausible value ranges of the major transition and intervention parameters are summarized in Table 6 in Section 7.1; the influence of these values on the conclusions is further examined by the threshold sensitivity analysis in Section 7.5.

5.3. Correction Factor of Closed-Loop Intervention

This section is the model. Whether the subclinical state can bring health benefits after being discovered depends on these three links working together.

Detection rate δ : The monitoring system (or the owner 's naked eye observation) can identify the probability of abnormalities when the pet is in the S state. Implementation compliance rate ρ: After identifying abnormalities, the owner actually performs the proportion of care or medical treatment as recommended. Response delay τ : The time interval between identifying an exception and performing an intervention, in days.

If any link is not strong enough, the intervention will fail. Even if implemented immediately, the effect of intervention is not necessarily 100%. Bioavailability is expressed as ε_0; the delay also makes the effectiveness decrease over time. Put them together, the definition of the effective factor of closed-loop intervention is obtained.

$$\varphi=\delta \cdot \rho \cdot \varepsilon_0 \cdot e^{-\lambda\tau} \tag{13}$$

Where λ is the delayed attenuation coefficient. The intuitive meaning of φ is: the degree of risk reduction corresponding to effective treatment in animals in the subclinical state. The modified sub-clinical-to-clinical transition probability is

$$p_{SC}=p_{SC}^{(0)}(1-\varphi) \tag{14}$$

This paper takes $\varepsilon_0 = 0.65$, which means that the risk of progress in the month is reduced by 65% under zero delay, which is the baseline biological effectiveness; $\lambda = 0.05$/day, and the effect was reduced by about half when the delay was 14 days.

Here I want to emphasize: even if the detection rate of monitoring equipment δ is very high, as long as the owner sees the reminder but does not act (ρ low), or takes a long time to act (τ large), φ will still be small. The value of early warning must be implemented before it is realized. This sentence will be repeated in this article.

5.4. The Setting of Three Comparative Scenarios

In order to quantitatively compare different modes, this paper sets up three situations (see Table 4). The difference between ρ and τ is the difference between manual operation and automatic operation of equipment linkage. These three parameter values are assumed and have not been actually measured. The matter will be discussed in detail in Section 8.2.

Table 4. parameter setting of three intervention scenarios

Scenario	Detection Rate(δ)	Compliance Rate(ρ)	Delay (τ)	Autoexec	Explanation
Mode A Traditional Manual Observation	0.35	0.30	45 Days	Nil	It was found by the naked eye in the middle and late stages, most of which had progressed before being noticed.
Mode B Open-Loop Intelligent Monitoring	0.80	0.45	7 Days	Nil	The device can discover, but only push reminders, relying on the pet owner to perform their own.
Mode C Closed-Loop Intelligent Monitoring	0.90	0.90	0.5 Days	Yes	After early warning, basic nursing was directly completed by equipment linkage.

5.5. Queue Recursion and Health Output Indicators

Let all queues be in a healthy state at the initial time, that is, $\pi(0)=(1,0,0)$. The monthly state distribution $\pi(t)=(\pi_H(t),\pi_S(t),\pi_C(t))$ is obtained by recursive $T=36$ months according to $\pi(t+1)=\pi(t)P$. This paper sets three outcome indicators:

(1) What is the cumulative clinical incidence rate in 3 years. Because C is in the absorption state, the probability of being in the clinical state at the last follow-up is the cumulative incidence rate:

$$\text{Incidence}=\pi_C(T) \tag{15}$$

(2) The average duration in different states (unit: month). The state probability of each month can be summed up month by month. In 3 years, how many months are healthy:

$$m_j=\sum_{t=1}^{T}\pi_j(t), \quad j\in\{H,S,C\}, \quad \sum_j m_j=T \tag{16}$$

(3) QA-HLM, that is, life months with quality after adjustment. Different health status has different quality of life, the introduction of utility weight $u_H=1.00$, $u_S=0.80$, $u_C=0.50$, get

$$\text{QA-HLM}=\sum_{t=1}^{T}[u_H\pi_H(t)+u_S\pi_S(t)+u_C\pi_C(t)] \tag{17}$$

QA-HLM includes both the benefits of prolonging healthy survival time and improving the quality of life. Use it to do the cost-benefit analysis of the effect indicators, in the conversion of adulthood is E=QA−HLM/12. How is the utility value determined? To be honest, I am estimated, 1.00,0.80,0.50 are given based on experience. Section 8.2 will deal specifically with this weakness.

6.Closed-Loop Intervention Cost-Effectiveness Evaluation Model

6.1. Cost Structure

Unified cost assumptions are defined for all three modes before calculation. Mode A refers to traditional manual observation. Since subclinical status is difficult to identify, there is no regular subclinical nursing cost, and costs only occur after pets enter the clinical state. Mode B and Mode C can identify subclinical status, so continuous subclinical nursing costs will be generated. All three modes follow the same calculation rules for equipment cost, subscription fee, subclinical nursing cost, one-off clinical treatment cost and long-term maintenance cost. The one-off clinical treatment cost C_{treat} in Table 5 represents the cost for a single clinical episode, with the unit of CNY per time. The time horizon of this base-case analysis is 36 months.

Regarding the zero subclinical nursing cost of Mode A in Table 10: although Mode A also assumes partial detection ($\delta = 0.35$) and intervention compliance ($\rho = 0.30$), the resulting detections occur only occasionally and late in the subclinical period, and the corresponding care consists of owner-initiated daily adjustments (e.g., diet and activity changes) rather than a structured nursing programme; this kind of sporadic expenditure is already contained in the routine daily feeding and housing cost that is common to all three modes, so no separate subclinical nursing item is modelled for Mode A. In contrast, Modes B and C identify the subclinical state explicitly and therefore trigger standardised nursing inputs (prescription food, health products and regular reviews in Table 5), which are accrued according to the months spent in the subclinical state. This assumption is conservative for the closed-loop modes: if a corresponding nursing cost were charged to Mode A as well, the total cost of Mode A would rise and the incremental advantage of Modes B and C would be understated rather than overstated. All cost items in Tables 5, 10 and 11 use CNY as the monetary unit, and the same definitions and calculation rules are applied across the three scenarios.

In the total cost of 3 years, equipment and subscriptions are fixed costs, and care and treatment are state-related costs. The fixed expenditure is directly included according to the business plan pricing; state-related expenditures are associated with the output of the Markov model-subclinical stay months to determine care costs, cumulative incidence to determine one-time treatment costs, and clinical stay months to determine maintenance costs. The reason for the treatment is very simple. Mode A has no equipment and subscription fees, but it ultimately has to bear the high cost of treatment and maintenance. If we only consider the front end without considering the back end, the horizontal comparison will be systematically biased towards the traditional observation.

$$C_{total}=C_{dev}+3\,C_{sub}+\frac{C_{care}}{12}m_S+C_{treat}\cdot\ \text{Incidence}+\frac{C_{maintain}}{12}m_C \tag{18}$$

The equipment fee and subscription fee are calculated as 3 years; the care fee was only generated when the pet was found, entered the S state and received care, so multiplied by the number of months of sub-clinical stay and divided by 12; one-time treatment costs multiplied by the cumulative incidence; maintenance fee multiplied by the number of months of clinical stay. Each unit price is shown in Table 5. Equipment 850/899 yuan, subscription 138/199 yuan from the project team business plan, belongs to the self-citation; treatment 9800 yuan/time, maintain 4500 yuan/year with reference to the pet hospital public charges, but did not do a multi-center price survey. These

numbers should be regarded as the benchmark hypothesis, and the break-even calculation in Section 7.4 will give the sensitive range of price changes.

The unit price is determined by referring to the product pricing of the business plan and the public charging level of the pet hospital. The specific values are shown in Table 5. Here, Model A is also included in the diagnosis and treatment costs it will eventually bear, otherwise the horizontal comparison is unfair.

Table 5. unit cost and utility parameters

Parameter	Taking Values	Explanation
C_{dev}	Mode A: 0 yuan; Mode B: 850 yuan; Mode C: 899 yuan	Business plan advanced version of hardware pricing.
C_{sub}	Mode A: 0 yuan/year; Mode B: 138 yuan/year; Mode C: 199 yuan/year	Platform subscription service fee.
C_{care}	800 yuan/year	Subclinical prescription food, health care products and review.
C_{treat}	9800 yuan/year	The one-off clinical treatment cost per clinical episode (unit: CNY per time).
$C_{maintain}$	4500 yuan/year	Long-term medication and review maintenance costs after diagnosis.
u_H,u_S,u_C	1.00,0.80,0.50	Three-state utility weight.

6.2. Effect Index

The effect index was adjusted to healthy life month with the quality of Section 5.5 and converted to year :

$$E=\frac{\text{QA-HLM}}{12} \quad \textbf{(unit: QA-HLM year)} \tag{19}$$

The reason for choosing it rather than simply using the incidence rate to measure is that the incidence rate can only reflect the aspect of whether there is a disease. The number of months of survival with disease and mild discomfort in the subclinical state are not shown in the incidence rate, but the part that early intervention can improve is among them. The benefits of extending healthy survival time and improving quality of life through QA-HLM can enter the denominator together.

6.3. Incremental Analysis and Decision Criteria

According to the framework of Section 2.4, taking Mode A (traditional manual observation) as the reference standard, this paper calculates the incremental cost ΔC, incremental effect ΔE and ICER of Mode B and C relative to Mode A :

$$\Delta C=C_X-C_A, \quad \Delta E=E_X-E_A, \quad \text{ICER}=\frac{\Delta C}{\Delta E}, \quad X\in\{B,C\} \tag{20}$$

In accordance with the provisions of Table 2, no longer repeated one by one. The only thing to explain separately is negative ICER: when $\Delta C < 0$ and $\Delta E < 0$, ICER takes a negative value. At this time, the essence of decision-making is ' whether the money saved is worth offsetting the loss of health benefits '. The correct judgment is that it is only accepted when $| ICER | > \lambda 0$. This paper also gives the results of the increase of mode C compared with mode B to answer how the closed-loop effect is better than the open-loop effect. In addition, a break-even analysis is carried out to find out the extent to which the price of mode C equipment can be reduced to $\Delta C \leq 0$, and no expenditure is increased in the case of $\Delta E > 0$.

7. Simulation Experiments and Results Analysis

7.1. Experimental Environment and Parameter Settings

The key parameters adopted in this Markov model are summarized in Table 6. The experiment is completed in the Python3.13 + NumPy environment. The Markov queue is recursive to deterministic calculation, and the results can be completely reproduced. At present, there is still a lack of public pet subclinical long-term follow-up cohort data at home and abroad, so this paper uses parametric simulation verification. In the first model, a simulated monitoring sample of n = 3000 pets was generated. In this study, 3000 virtual pet samples were generated based on Beta distribution for simulation verification. For each of the 12 monitoring indicators, two groups of shape parameters for the Beta distribution were assigned separately for healthy and subclinical pets according to pet physiological reference ranges. The parameters constrain the indicator deviation values within the interval [0,1]. Samples were stratified-sampled: 35% of all samples were predefined as subclinical state at baseline, and the remaining 65% were defined as healthy state. No sample was initialized to clinical state; all clinical-state observations were produced through monthly state transition of the Markov model rather than direct sampling. For healthy samples, indicator deviations concentrate near zero; for subclinical samples, the distribution shifts toward higher-deviation region without reaching clinical diagnostic thresholds. The simulated dataset is only used to verify the discriminant logic of risk-scoring model, and the obtained AUC cannot be directly equivalent to real-world clinical performance. Specifically, the baseline shape parameters were set to $\alpha = 2$, $\beta = 8$ for healthy pets, so that the indicator deviations concentrate around 0.15–0.25, and to $\alpha = 5$, $\beta = 4$ for subclinical pets, so that the deviations concentrate around 0.50–0.60; to reflect the physiological differences among the 12 indicators, the shape parameters of each indicator were perturbed within ±20% around these baseline values. The subclinical labels were assigned before data generation: the 3,000 simulated pets were divided by stratified sampling, with 35% (1,050 pets) randomly designated as subclinical and the remaining 65% (1,950 pets) as healthy, and the 12 indicator deviations of each pet were then generated from the Beta distribution of its assigned class. Each pet contained an individual deviation degree of 12 indicators. The potential health defects obeyed the Beta distribution and were segmented by quantiles. The proportion of subclinical samples was designed to be 35%. This set of data is only used to test whether the discriminant logic of the scoring model is valid, and AUC is not equivalent to real clinical sensitivity. Model 2 uses the deterministic cohort recursion in Section 5.5. The transition

probabilities are p_{HS}=0.020 , p_{SH}=0.050 , and $p_{SC}^{(0)}$=0.100 , and the intervention parameters are ε_0=0.65 and λ=0.05/day. The δ, ρ, and τ of the three scenarios are shown in Table 4. Follow-up T = 36 months. The unit cost and utility weight of the third model are shown in Table 5, and the payment threshold is λ_0 = 10000 yuan/QAHLY.

Table 6. Summary of key model parameters

Parameter	Symbol	Value	Source
Monthly transition probability from healthy to subclinical	p_{HS}	0.020	Veterinary expert elicitation and scenario assumption
Monthly transition probability from subclinical to healthy	p_{SH}	0.050	Veterinary expert elicitation and scenario assumption
Baseline monthly transition probability from subclinical to clinical	$p_{SC}^{(0)}$	0.100	Veterinary expert elicitation and scenario assumption
Biological effectiveness of intervention	ε_0	0.65	Scenario assumption
Delay attenuation coefficient	λ	0.05 per day	Scenario assumption
Detection rate (Mode A/B/C)	δ	Mode A:0.35; Mode B:0.80; Mode C:0.90	Scenario assumption
Compliance rate (Mode A/B/C)	ρ	Mode A:0.30; Mode B:0.45; Mode C:0.90	Scenario assumption
Response delay (Mode A/B/C)	τ	Mode A:45 days; Mode B:7 days; Mode C:0.5 days	Scenario assumption

7.2. Model 1 Results : Weight Distribution and Discriminant Performance

The entropy value and weight of the 12 indicators are shown in Table 6, and the visualization of the weight distribution is shown in Figure 1.

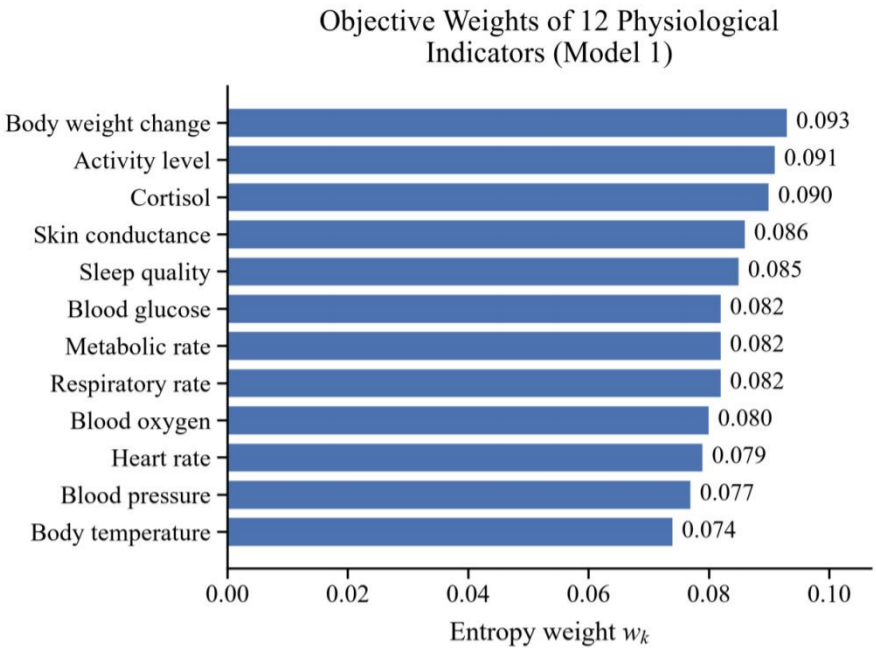


Figure 1. 12 index entropy weight method weight distribution

Table 6 is the entropy value and weight of 12 indicators, and Figure 1 is the weight distribution map. The weight was mainly between 0.074 and 0.093, and the difference between the maximum (weight change 0.0926) and the minimum (body temperature 0.0741) was less than 25%. The balance can be understood as a strong complementarity between the 12 indicators, but there is a limitation: the dispersion of the deviations generated by the Beta distribution used in the simulation experiment is artificially set to be very close, so the entropy weight method will naturally come close to equal weight results. The dispersion degree of each index in the real queue may be more different, so the weight structure should also be re-calibrated.

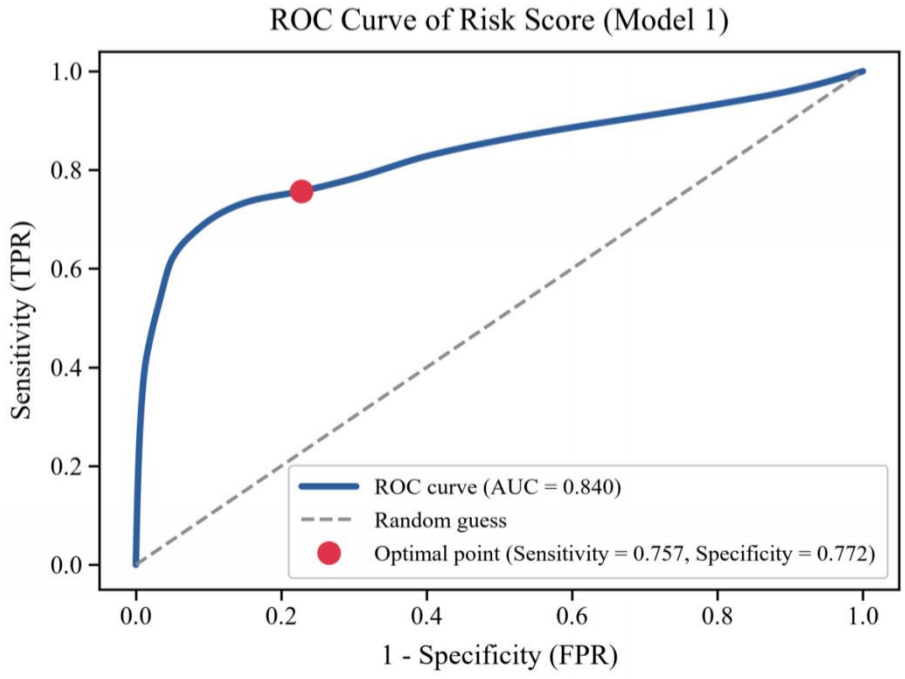


Figure 2. risk score ROC curve

Table 7. 12 indicators of entropy and weight (model 1)

Serial Number	Index	Entropy e_k	Weight w_k	Serial Number	Index	Entropy e_k	Weight w_k
1	Blood Sugar	0.9575	0.0821	7	Arterial Oxygen	0.9588	0.0797
2	Cortisol	0.9532	0.0905	8	Blood Pressure	0.9604	0.0766
3	Heart Rate	0.9590	0.0793	9	Metabolic Rate	0.9578	0.0817
4	Body Temperature	0.9617	0.0741	10	Body Weight Change	0.9521	0.0926
5	Respiratory Rate	0.9578	0.0817	11	The Amount of Activity	0.9530	0.0910
6	Skin Conductivity	0.9558	0.0856	12	Sleep Quality	0.9559	0.0852

Table 8. risk score discriminant performance

Index	Numerical Value
AUC	0.8395
Youden Optimal Threshold	0.0934
Sensitivity Under This Threshold	0.7571
Specificity Under This Threshold	0.7718
Accuracy Under This Threshold	0.7667
Youden Index	0.5289
High Sensitive Working Point Threshold	0.0770
Sensitivity Under This Threshold	0.9000
Specificity Under This Threshold	0.5062

The discriminant performance is shown in Table 7 and Figure 2. The AUC is 0.8395, which belongs to the upper-middle level of judgment ability, indicating that the weighted score can distinguish subclinical patients, but there is still a certain gap from the perfect recognition. When the threshold was taken according to the Youden index, the sensitivity and specificity were about

0.76. If the sensitivity is increased to 0.90 and the specificity is reduced to 0.5062 according to the screening principle of priority without missed diagnosis, about half of healthy pets will be listed for observation. This choice can not be avoided in engineering. Single threshold alarm must make a trade-off between sensitivity and specificity when AUC = 0.84, while three-level stratification plus multiple confirmation is more in line with the actual situation than one threshold. The design of hierarchical early warning in the third section of the third chapter is based on this point.

See the risk stratification results in Table 8 The actual subclinical ratio of the low-risk group was 8.50%, the medium-risk group was 27.40%, and the high-risk group was 69.10%, which was about 8.1 times that of the low-risk group. By prioritizing early warning resources to high-risk groups, the hit rate is more than twice as high as treating everyone indiscriminately. Hierarchical push is not a simple form of classification; it is a clear allocation of resources.

7.3. Results of Model 2: Comparison of The Course of Disease in Three Scenarios

Chapter 5, the results of the 36-month follow-up (see Table 9 and Table 10) and the cumulative incidence curve (see Figure 3) can be obtained. Comparing the three sets of φ values together, the difference between them is much larger than the difference of δ : the range of δ is 0.35 ~ 0.90, which has only more than doubled, while φ jumps from 0.0072 to 0.5135, with a difference of nearly 70-fold. The amplification effect comes from the superposition of ρ and τ. The ρ of mode A is 0.30, and the τ is 45 days. After the multiplication of the two, the detection ability is almost completely offset. The ρ of mode C is close to 1, τ is shortened to half a day, and φ can be realized. That is to say, if the improvement of the perception end does not go through the execution end, there is almost no healthy benefit in the model.

Table 9. 3 risk stratification and actual subclinical ratio

Risk Level	Rating Range	Sample Size	Proportion	The Actual Sub-Clinical Proportion
Low Risk	$R < 0.075$	1, 000	33.3%	8.50%
Intermediate Risk	$0.075 \leq R < 0.101$	1, 000	33.3%	27.40%
High Risk	$R \geq 0.101$	1, 000	33.3%	69.10%

However, this conclusion depends on the set value in Table 4. Mode B ρ = 0.45, τ = 7 days, Mode C ρ = 0.90, τ = 0.5 days, these are scenario settings, not estimated from real user behavior data. If the ρ of mode B is actually 0.60, the gap will be narrowed. ' Closed-loop is better than open-loop ' is mathematically the inference of these settings, not independent of the hypothesis. The real gap needs to be calibrated by user behavior data, which will be limited in Section 8.1.

The number of cases has decreased a lot, and the more backward the gap is greater. The 3-year cumulative incidence was 31.29% for A, 28.86% for B, and 21.18% for C, respectively. Compared with the traditional observation, the closed-loop is absolutely reduced by 10.11 percentage points, the relative reduction is 32.3 %, and the relative reduction is 26.6% compared with the open-loop.

As shown in Figure 4, after the tenth month, the three curves began to be significantly separated, and increased in one direction with the increase of time, which was in line with the law of ' early input and late harvest ' of chronic disease intervention.

Table 10. three scenarios markov model results (36 months)

Index	Mode A Traditional Observation	Mode B Open-Loop Monitoring	Mode C Closed-Loop Monitoring
Intervention Effective Factor φ	0.0072	0.1649	0.5135
Modified Monthly Transition Probability p_{SC}	0.09928	0.08351	0.04865
3-Year Cumulative Clinical Incidence	31.29%	28.86%	21.18%
Health State Staym_H(Month)	27.50	27.67	28.16
Subclinical Staym_S(Month)	3.24	3.56	4.49
Clinical State Staym_C(Month)	5.27	4.77	3.34
QA-HLM(Month)	32.72	32.90	33.43
QA-HLM(Year)	2.7266	2.7418	2.7858

The course of the disease is compressed to the subclinical stage, which is worth noting. The subclinical residence time of mode C was the longest (4.49 months), while the clinical residence time was the shortest (3.34 months). This is not bad news : closed-loop intervention postpones a large number of cases that have entered the clinical stage to a controlled, reversible and low-cost subclinical stage, replacing the ' high clinical stage ' with an ' additional managed subclinical stage '. Subclinical stay is too long will produce the problem of increased care costs, this account by the model three to calculate.

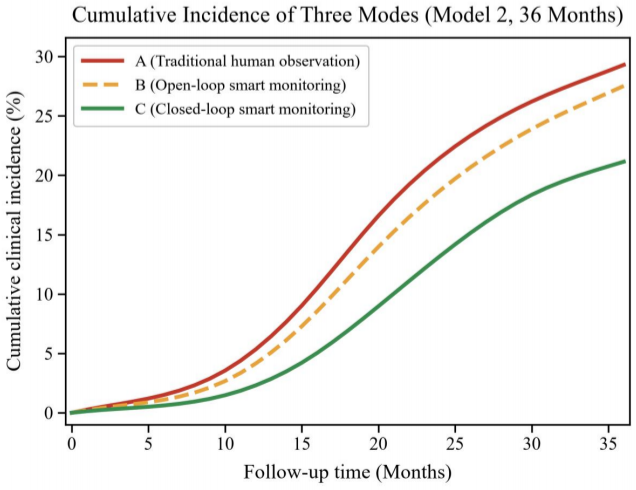


Figure 3. cumulative clinical incidence curve of three scenarios

7.4. Model Three Results : Cost and Effect Evaluation

According to the unit cost of Table 5, the per capita cost of 3 years can be calculated, and the cost composition (see Table 11), cost-effectiveness plane (see Figure 4) and the results of incremental analysis (see Table 12) can be obtained.

Table 11. three scenarios 3-year per capita cost composition (yuan)

Cost Item	Mode A	Mode B	Mode C
Equipment Purchasing	0.0	850.0	899.0
Subscription Service (3 Years)	0.0	414.0	597.0
Subclinical Nursing	0.0	237.0	299.6
Clinical One-Time Treatment	3066.1	2828.0	2075.6
Clinical Maintenance	1974.8	1790.6	1254.0
Footing	5040.9	6119.6	5125.2

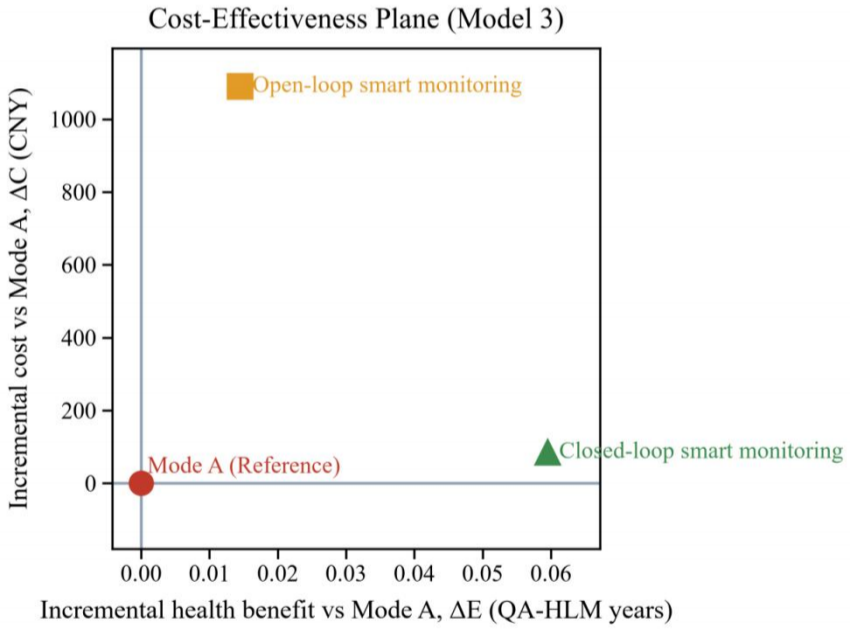


Figure 4. incremental cost-effectiveness plane (with reference to model A)

Open-loop mode B is technically feasible, but it is not cost-effective from an economic point of view. Mode B is 1078.7 yuan more than Mode A (including hardware costs, subscription costs, and subclinical care), but only 0.0152 QA-HLM years (about 5.6 days) are increased, and ICER reaches 70967 yuan/QAHLY, more than seven times the standard of 10,000 yuan. It can be seen from the parameters that the front-end can detect anomalies ($\delta = 0.80$), but the proportion of pet owners doing things according to the prompt is very low ($\rho = 0.45$), and the average delay is 7 days, so the health benefits are weakened, but the hardware costs and subscription fees are not reduced. This is

the reason why simple reminder products are difficult to be recognized by the market. However, it should be noted that if the threshold is set to double the per capita GDP, that is, about 70,000 yuan, 70,967 is only slightly greater than this threshold, and the conclusion will change from ' uneconomical ' to ' reluctantly ' under Model B. Section 7.5 gives the results of the threshold sensitivity.

Table 12. results of incremental cost-effectiveness analysis

Compare	ΔC (Element)	ΔE (QA-HLM Years)	ICER (Yuan/QAHLY)	Decision
Mode B Contrast Mode A	+1078.7	+0.0152	70967.1	No Cost-Effectiveness (Far Beyond the Threshold)
Mode C Contrast Mode A	+84.3	+0.0592	1424.0	Cost-Effective (Well Below 10000 Threshold)
Mode C vs. Mode B	−994.4	+0.0440	−22600.0	Strictly Dominant (Cheaper and Better)

The closed-loop mode C is close to cost neutrality and has a high cost performance. The C mode costs 84.3 yuan more than A, but can get 0.0592 QA-HLM years (about 21.6 days), ICER is 1424 yuan/QAHLY, less than 1/7 of the standard of 10,000 yuan. Strictly speaking, it does not belong to the money-saving scheme ($\Delta C > 0$), but considering that mode C can also provide additional functions such as positioning anti-lost, behavior recording, and remote viewing, the 84 yuan difference between the three years can basically be ignored.

Compared with mode B, mode C is a strict advantage, saving 994.4 yuan, and obtaining 0.044 QA-HLM years more, which is in the ' better cost-saving ' quadrant ($\Delta C0$) of the cost-benefit coordinate system. The ICER of this line cannot be written directly as-22600, and the meaning of negative ICER in different quadrants is different, which can be directly marked as ' strictly dominant '. The implication of this result for product design is that it is more effective to put the same amount of money into automated execution to improve the compliance rate than to accumulate more expensive sensors to improve the detection rate. However, it should be noted that this conclusion depends on the different values of ρ and τ.

The break-even price can be reversely derived from Table 11. $\Delta C = 84.3$ yuan, that is, the price of mode C equipment is reduced from the original 899 yuan to 814.7 yuan (reduced by about 9.4%), which can make $\Delta E > 0$ and $\Delta C \leq 0$, and find a balance between saving money and improving efficiency. Therefore, we can price the basic/advanced version of the business plan (399 yuan/899 yuan), and give the corresponding discount according to the number of bulk purchases of pet hospitals, or cooperate with insurance companies to provide certain subsidies.

8.Summary and Prospect

8.1. Main Results

The 12 weight values obtained by the entropy weight method were between 0.0741 and 0.0926, and the AUC value of the risk score was 0.8395. The actual incidence of subclinical in the low, medium and high risk groups was 8.50%, 27.40% and 69.10%, respectively. The method of multi-index fusion and hierarchical push can be used in the simulation data, but the weight balance is likely to be caused by the way of data generation, which needs to be re-calibrated in the real queue.

Secondly, in the three scenarios, the 3-year cumulative clinical incidence rate was 31.29% for the traditional observation method, 28.86% for the open-loop monitoring method, and 21.18% for the closed-loop monitoring method. The closed-loop was 32.3% lower than the traditional observation. The decrease depends on the values of δ, ρ and τ given in Table 4, and is not independent of assumptions.

Third, the closed-loop is better than the open-loop : the cost is 994.4 yuan, the effect is 0.0440 QA-HLM years. Compared with the traditional ICER of 70967 yuan/QAHLY, the open-loop has no promotion value under the conservative threshold of 10,000 yuan, but it is at the edge under the threshold of 1 times per capita GDP; the closed-loop ICER is only 1424 yuan/QAHLY, which is cost-effective under three thresholds.

Fourthly, the problem lies in implementation rather than cognition. The benefit of δ increasing by 12.5% is far less than that of ρ increasing by 100% and τ decreasing. When ρ is equal to 1, the total cost of the closed-loop mode is 4863.1 yuan less than the traditional mode of 5040.9 yuan without monitoring. The most practical finding of this paper is this conclusion, but it is also a conclusion drawn under the scenario setting. The real gap depends on the user behavior data.

8.2. Research Insufficiency and Prospect

The conclusion of this paper is based on the simulation parameters, which is the biggest limitation of this paper: the transition probability and cost parameters can only be set according to the literature and business plan, and have not been verified by the real queue; the utility weights Us and Uc are set values, and the VetMetrica scale is not used for measurement; the differences between scenario parameters δ, ρ and τ are assumed rather than measured. The economic evaluation only does deterministic analysis and does not do probabilistic sensitivity analysis (PSA), which still has a certain gap with the requirements of CHEERS 2022. The following research can be carried out from five aspects. One is the real cohort verification. A prospective follow-up cohort was established at the pet hospital, and the transition probability matrix and cost parameters were determined by the real cohort. The second step is to introduce age-dependent transition probabilities to break the homogeneous Markov assumption or use a semi-Markov model. The third is to improve the utility measurement, using pet-specific health-related quality of life scales such as VetMetrica, and to determine Us and Uc through the owner 's questionnaire. Fourth, in the cost model, the cost of misreporting and the decline in trust, ineffective treatment and long-term use of attention are taken into account. The fifth aspect is to explore the insurance linkage mechanism. According to the results of cost saving in this paper, the insurance sharing model of equipment subsidy-claim

reduction is designed. Shapley value can be used to analyze the income distribution of pet owners, hospitals, manufacturers, insurance and platforms.

Author Contributions:

Conceptualization, M.L.; methodology, M.L.; validation, M.L., Y.D.; formal analysis, M.L.; resources, M.L.; writing—original draft preparation, M.L.; writing—review and editing, M.L., Y.D.; project administration, M.L.; funding acquisition, M.Liu.; investigation, Y.D.; visualization, Y.D.; software, S.W.; data curation, S.W.; supervision, M.S. All authors have read and agreed to the published version of the manuscript.

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Conflict of Interest:

The authors declare no conflict of interest.

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