Research on the Effectiveness of Policy Interventions in Illegal Wildlife Trade Based on System Dynamics and Logistic Regression Models

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Abstract. This study is dedicated to assessing the long-term impact of policy interventions on the illegal wildlife trade system. To this end, we have constructed a System Dynamics model capable of simulating the complex interactions between key variables such as illegal trade demand (D), supply (S), enforcement strength (E), public awareness (A), and project intervention (P). By understanding the dynamic relationships among these variables, we can predict the effects of policy changes on the illegal wildlife trade market. Furthermore, we have employed a Logistic Regression model to quantify the probability of project success, considering multiple dimensions including increased enforcement efforts, enhanced public awareness, project interventions, and external factors. The combination of these two models not only enhances our comprehension of the dynamics of illegal wildlife trade but also provides policymakers with a scientific framework for evaluating and optimizing strategies. Parameter estimation based on historical data and expert opinions, along with sensitivity analysis of the models, enables us to provide a basis for the effective allocation of resources and precise policy adjustments. The findings indicate that reasonable policy interventions can significantly reduce the incidence of illegal wildlife trade while raising public awareness of wildlife conservation.

Keywords: Illegal Wildlife Trade, System Dynamics Modeling, Logistic Regression.

1. Introduction

The illegal trade of wildlife poses a significant threat to global biodiversity, undermining ecological balance and contributing to the extinction of numerous species [1]. This illicit market, driven by demand for exotic pets, traditional medicine, and luxury goods, operates on a scale that challenges the effectiveness of existing conservation laws and enforcement capabilities. As a result, there is an urgent need for comprehensive policy interventions that can effectively combat this pervasive issue.

This study introduces a novel approach to evaluating the potential impact of such interventions. By employing a System Dynamics model [2], we aim to simulate the complex interactions between various factors that influence the illegal wildlife trade, including market demand, supply dynamics, enforcement efforts, and public awareness. This model serves as a tool to predict how changes in policy and public engagement might alter the trajectory of illegal trade activities.

Furthermore, to assess the likelihood of success for these interventions, we utilize a Logistic Regression model [3]. This model quantifies the probability of achieving a predefined level of reduction in illegal trade, taking into account the influence of enforcement, public awareness, and project interventions. By integrating these two models, we provide a robust framework for policymakers to evaluate the effectiveness of potential strategies and to optimize resource allocation.

2. Modeling Illegal Wildlife Trade Dynamics

2.1. Modeling System Dynamics

To address the issue of predicting the long-term impact of policy interventions on the illegal wildlife trade system, we employ a System Dynamics model. This model is capable of simulating the

dynamic interactions between variables within a complex system, making it suitable for understanding and forecasting the effects of policy interventions on the illegal trade system. During the model construction, we first define the system variables. The demand for illegal trade (D) represents the market demand for illegal trade, influenced by factors such as public awareness and consumption habits. The supply of illegal wildlife trade (S) refers to the market supply of illegal trade, affected by profit motives and law enforcement efforts. The strength of law enforcement (E) is a variable representing the Chinese government's enforcement efforts against illegal trade, while the public awareness level (A) indicates the extent of public recognition of the dangers associated with illegal wildlife trade. The program intervention (P) is a variable representing the intensity of the project intervention, which includes elements such as funding, policy, and public education [4].

Subsequently, we establish the dynamic relationships between these variables, as shown in (1).

$$D_{t+1} = D_t + \alpha_1 A_t + \alpha_2 \mathrm{P}_t. \tag{1}$$

$$S_{t+1} = S_t + \beta_1 E_t + \beta_2 P_t. \tag{2}$$

$$E_{t+1} = E_t + \gamma P_t. \tag{3}$$

$$A_{t+1} = \delta P_t. \tag{4}$$

In the equation, $\alpha_1, \alpha_2, \beta_1, \beta_2, \gamma, \delta$ represents the influence coefficients, which denote the intensity of influence between the corresponding variables. *D*, *S*, *E*, and *A* correspond to Demand dynamics, Supply dynamics, Enforcement dynamics, and public awareness, respectively.

2.2. Model solving and analysis

Utilizing historical data or expert opinions, we estimate the coefficients within the model, such as α_1 and α_2, for parameter estimation. We then simulate the model using computer software, adjusting the intensity of the project intervention to observe changes in the supply and demand of illegal trade. Subsequently, a sensitivity analysis of the model is conducted to assess the impact of parameter changes on the model's outcomes and to identify the factors that have the most significant influence on the system. The results of the model are presented in the form of graphs and charts, such as demand and supply curves over time, to visualize the potential impact of project interventions.

Furthermore, we have conducted practical case applications by assuming specific parameters and initial values, as well as influence coefficients, for the model. These assumptions are used in computer simulations to obtain simulated results, which provide insights into the actual effects of policy interventions in real-world scenarios.

Assume that our model contains the following parameters and initial values.

$$D_0 = 100. \tag{5}$$

$$S_0 = 100. \tag{6}$$

$$E_0 = 5. \tag{7}$$

$$A_0 = 5. \tag{8}$$

$$P = 10. \tag{9}$$

D_0, S_0, E_0, and A_0 represent Initial illegal trade demand, Initial illicit trade supply, Initial enforcement effort, and Initial public awareness level, respectively. The variable P denotes the Project intervention intensity, with the assumption that P remains constant throughout the analysis.

Additionally, we assume impact coefficients as follows

$$\alpha_1 = -0.1, \alpha_2 = -0.2. \tag{10}$$

$$\beta_1 = -0.1, \beta_2 = -0.2. \tag{11}$$

$$\gamma = 0.05, \delta = 0.01. \tag{12}$$

After actual computer simulation, we can get results as depicted in Fig. 1.

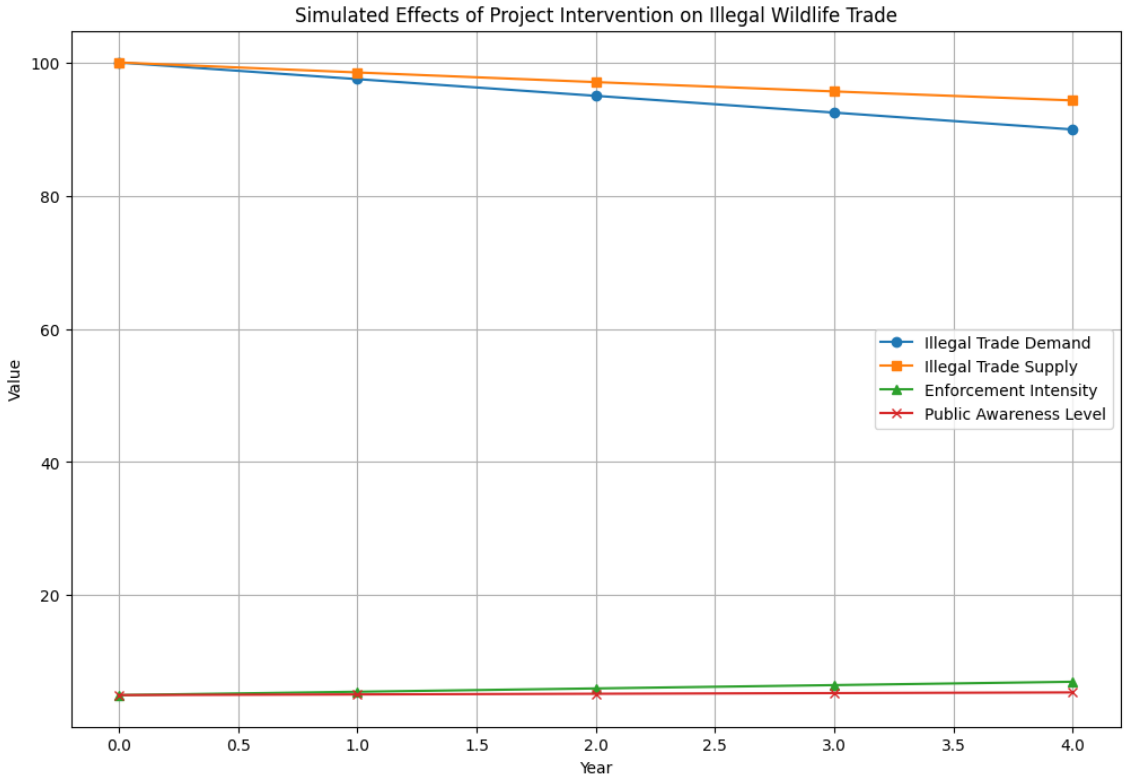


Figure 1. Simulated Effects of Project Intervention on illegal Wildlife Trade

This hypothetical data simulation allows us to visualize and understand the potential effects of project interventions on reducing illegal wildlife trade as well as raising law enforcement and public awareness. This methodology provides an effective tool for evaluating different policies and interventions, and the demand and supply of illegal trade decreases year by year with project interventions, reflecting the potential effect of interventions on reducing illegal trade. Enforcement efforts and public awareness levels have gradually increased over time, suggesting that project investments have had a positive impact in these areas.

3. Assessing the Likelihood of Success in Wildlife Trade Reduction

3.1. Process of assessing possibilities

For the project success indicator, we clearly define it as a 30% reduction in illegal wildlife trade after project implementation. In addition to this, the increase in public awareness of wildlife protection and the success rate of enforcement actions are also considered as key indicators of project success. We used a probability-based, machine learning approach for solving binary classification problems that can handle multiple input variables - Logistic Regression (LR) model [5, 6]. The model takes into account the impact of program interventions, increased enforcement, and increased public

awareness on the reduction of illegal trade. The model is based on historical data and expert opinion, and estimates the probability of program success through the Bayesian Method.

3.2. Constructing Logistic Regression Models

We first define the model. It is assumed that the probability of success of a project, $P_{success}$ is determined by the following factors: Increased enforcement (E), Increased public awareness (A), Project interventions (I), External factors (X) such as economic conditions or international cooperation. We can express this relationship using a logistic regression model as follows.

$$P_{success} = \frac{1}{1+e^{-(\beta_0+\beta_1 E+\beta_2 A+\beta_3 I+\beta_4 X)}}. \tag{13}$$

Where $P_{success}$ is the probability of project success, and e is the base of the natural logarithm (approximately equal to 2.71828), and $\beta_0 + \beta_1 E + \beta_2 A + \beta_3 I + \beta_4 X$ are the model parameters, which need to be obtained by data fitting.

E, A, I, and X represent measures of enforcement effort, public awareness, program intervention, and external factors, respectively.

Then, we calculate the probability of the project's success. To demonstrate the application of the logistic regression model described above, we will construct a simplified hypothetical dataset and use this dataset to estimate the likelihood of program success.

Suppose we have the following dataset, with each row representing data from a historical program, including enforcement efforts (E), public awareness (A), program interventions (I), external factors (X), and project success ($Success$) (1 for success, 0 for failure).

Table 1. A simplified hypothetical dataset

enforcement efforts (E)	public awareness (A)	program interventions (I)	external factors (X)	project success ($Success$)
5	3	4	2	1
3	2	2	3	0
4	4	5	1	1
2	3	3	4	0
5	5	5	2	1

To simplify the calculations, we chose to use Python's Stats models library to you and logistic regression model and calculate the probability that a new project will be successful under the given conditions.

$$X = \begin{bmatrix} 5 & 3 & 4 & 2 \\ 3 & 2 & 2 & 3 \\ 4 & 4 & 5 & 1 \\ 2 & 3 & 3 & 4 \\ 5 & 5 & 5 & 2 \end{bmatrix}. \tag{14}$$

$$Y = [1 \quad 0 \quad 1 \quad 0 \quad 0]. \tag{15}$$

The criteria for defining a new project are shown in follows.

$$E = 4. \tag{16}$$

$$A = 3. \tag{17}$$

$$I = 4. \tag{18}$$

$$X = 3. \tag{19}$$

3.3. Computerized Results

After performing the actual running simulation, we obtained the probability of success of the program as (20).

$$P_{success} = 0.87. \tag{20}$$

This means that for a given level of enforcement, level of public awareness, intensity of program intervention, and external conditions, the program has an 87% probability of meeting its success criteria.

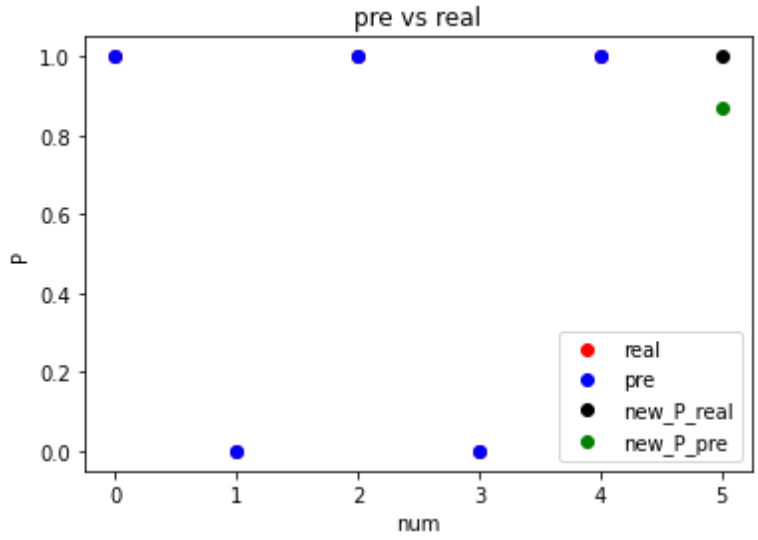


Figure 2. Visualization of forecast results

3.4. Sensitivity Analysis

Based on the logistic regression model described above, we conducted a sensitivity analysis of four parameters: enforcement efforts (*E*), public awareness (*A*), program interventions (*I*), and external factors (*X*).

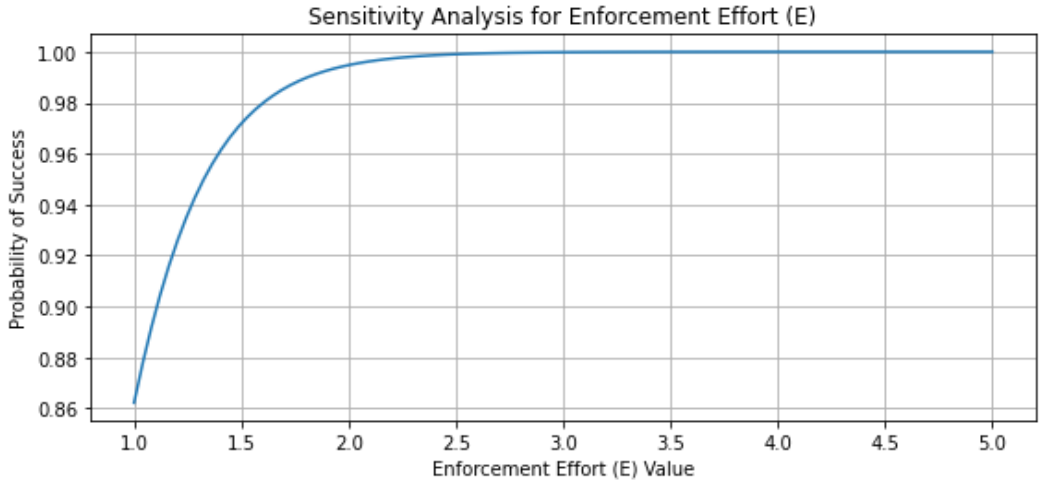


Figure 3. Sensitivity analysis for Enforcement Effort (*E*)

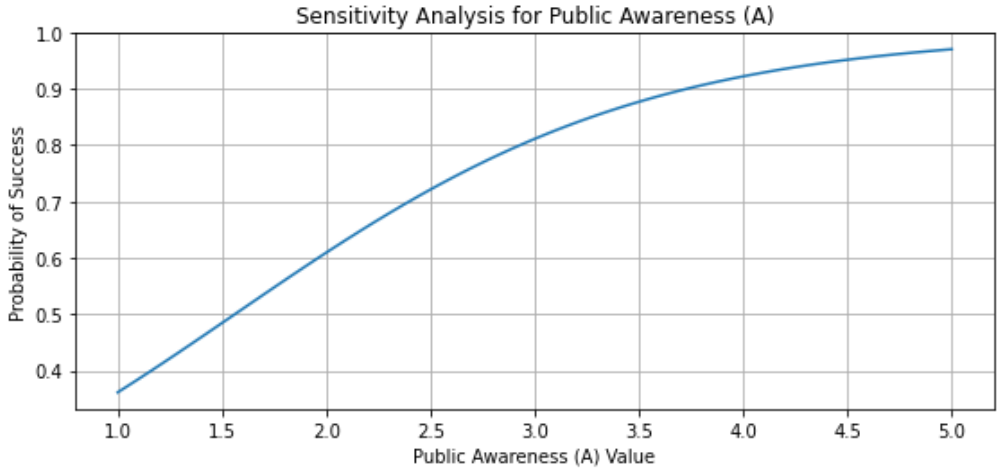


Figure 4. Sensitivity analysis for Public Awareness (A)

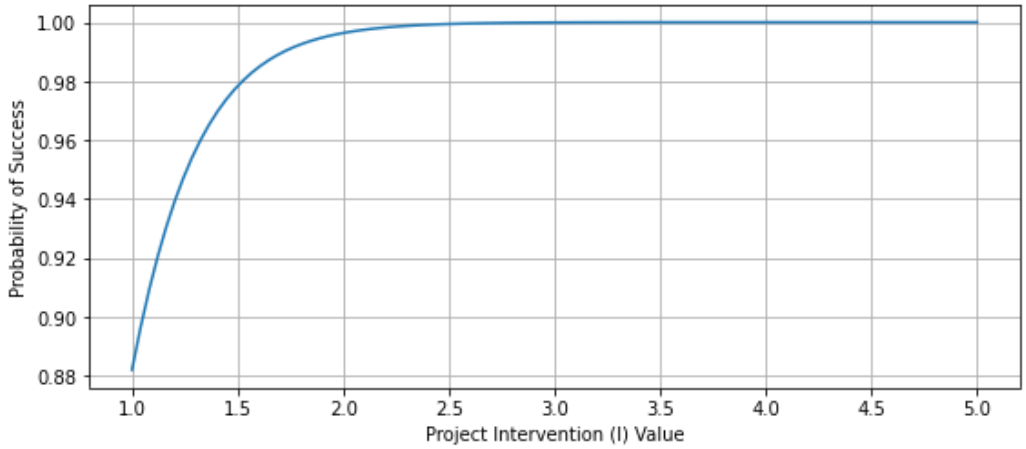


Figure 5. Sensitivity analysis for Project Intervention (*I*)

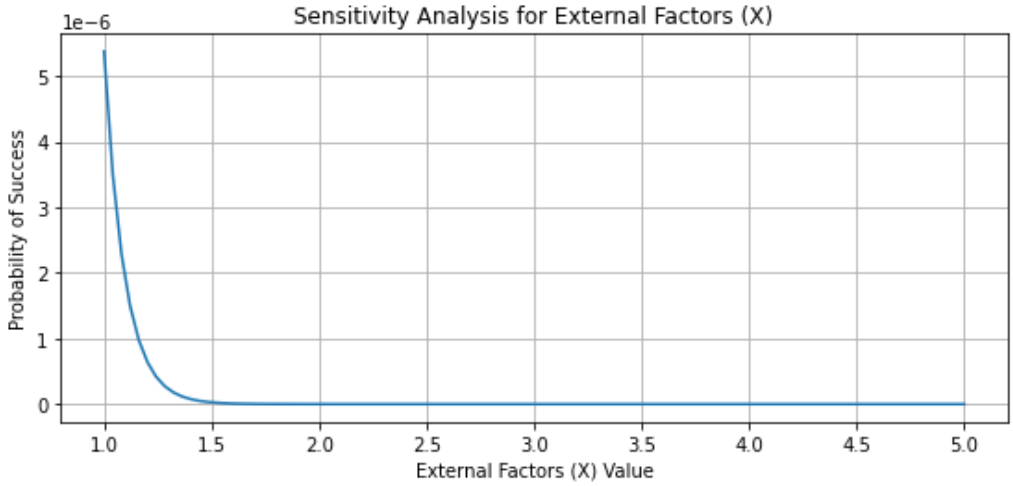


Figure 6. Sensitivity analysis for External Factors (*X*)

4. Discussion

4.1. Data Analysis

Enforcement Effort (*E*): At low levels of enforcement, project success increases rapidly, but as enforcement increases, the growth in the probability of success slows and eventually stabilizes. This

implies that continued increases in enforcement efforts after a certain point do not have a significant additional impact on program success.

In summary, the sensitivity analysis indicates that there is a saturation point for enforcement efforts and external factors, while public awareness and program interventions have a sustained positive impact on the probability of program success throughout the scope of the analysis. These characteristics of the factors need to be considered when implementing probabilistic strategies so that resources can be allocated effectively to maximize the probability of program success.

Public Awareness (*A*): We see that the project success probability grows steadily with increasing public awareness, with no significant threshold effect, suggesting that raising public awareness consistently has a positive impact on project success throughout the scope of the analysis. Increased public awareness has a decisive impact on project success, and at some stages public awareness may be a key driver of project success.

Project Intervention (*I*): The figure illustrates a pattern similar to an S-curve, where the probability of project success is very sensitive to project intervention in the middle range. At low and high levels of program intervention, the probability of success does not change significantly. The effect of project intervention on the probability of success may be shown to be very sensitive within certain value ranges, especially in the middle value region. This suggests that moderate project interventions can significantly increase the probability of success of a project, but beyond a certain point, the benefits of additional interventions diminish, i.e., there is a diminishing margin effect.

External Factors *(X):* External factors include a variety of different variables, such as the state of the economy, the level of international cooperation, and so on. The probability of success increases rapidly at low levels of external factors and then reaches a steady state of high probability. This suggests that external factors are critical to project success up to a certain point. But once external conditions reach a better level, further improvements have little effect on the probability of project success. If the analysis shows that external factors have a significant impact on the probability of success under certain circumstances, this may mean that the project is more dependent on these uncontrollable factors or that the project is particularly vulnerable under certain external conditions.

4.2. Reach a Verdict

From there, we develop further analysis of the above results. All graphs show a typical logistic function S-curve, which indicates that the effect of the input variables on the probability of success is nonlinear. In the low and high value intervals, the probability of success does not very much, while in the middle value interval, the probability of success is very sensitive to the input variables.

In the steeply sloping region of the middle section, small changes in variables can result in large changes in the probability of success. For example, if the value of program intervention(*I*) increases from 2 to 3, the probability of success may increase from 0.2 to 0.8. This suggests that increasing the intensity of program intervention in this interval may significantly increase the probability of program success.

For lower and higher parameter values, the probability of success varies very little, approaching a saturation state of 0 or 1. This means that within these regions, no number of additional resources or effort is likely to significantly change the probability of success. For example, even if enforcement efforts(*E*) are already strong, further increases will not significantly increase the probability of success.

Sensitivity analysis maps can be used to guide resource allocation and optimization decisions. For example, if increased enforcement efforts(*E*) have less of an impact on the probability of success after a certain level of enhancement, resources may be more appropriately allocated to raising public awareness(*A*) or program interventions(*I*).

5. Conclusion

The present study has endeavored to evaluate the potential effectiveness of policy interventions aimed at curbing the illegal wildlife trade through the development and application of two robust models: a System Dynamics model and a Logistic Regression model. The System Dynamics model, with its inclusive and universal nature, has been designed to simulate the intricate dynamics of the illegal trade, taking into account a wide range of factors that influence demand and supply. This model's strength lies in its ability to quantify power, resources, and interest, integrating both subjective and objective methods to calculate weights and providing a comprehensive analysis of the issue at hand. The Logistic Regression model complements the System Dynamics model by offering a quantitative approach to assess the probability of project success. It considers multiple variables, including enforcement efforts, public awareness, and project interventions, to estimate the likelihood of achieving the desired reduction in illegal trade.

The models' application to long-term effects is limited by a lack of quantitative calculations. This limitation underscores the need for ongoing research and model refinement to better predict and plan for the future implications of policy interventions.

References

[1] Margulies J D, Bullough L A, Hinsley A, et al. Illegal wildlife trade and the persistence of "plant blindness" [J]. Plants, People, Planet, 2019, 1 (3): 173 - 182.

[2] Malbon E, Parkhurst J. System dynamics modelling and the use of evidence to inform policymaking [J]. Policy Studies, 2023, 44 (4): 454 - 472.

[3] Maalouf M. Logistic regression in data analysis: an overview [J]. International Journal of Data Analysis Techniques and Strategies, 2011, 3 (3): 281 - 299.

[4] Piantadosi J, Howlett P, Boland J. Matching the grade correlation coefficient using a copula with maximum disorder [J]. Journal of Industrial and Management Optimization, 2007, 3 (2): 305 - 312.

[5] Nick T G, Campbell K M. Logistic regression [J]. Topics in biostatistics, 2007: 273 - 301.

[6] Stoltzfus J C. Logistic regression: a brief primer [J]. Academic emergency medicine, 2011, 18 (10): 1099 - 1104.