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Shakir Yahya Zakarya, Omer Paree khan Abdulla & Othman Sarween Asaad. Evaluation of Logistic and Poisson Regression Models in Analyzing Nursing Care Quality among Patients Undergoing Laparoscopic Cholecystectomy in Erbil City. ***University of Kirkuk Journal For Administrative and Economic Science*** **(2026) 16 (1):376-387.**

Evaluation of Logistic and Poisson Regression Models in Analyzing Nursing Care Quality among Patients Undergoing Laparoscopic Cholecystectomy in Erbil City

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Abstract: Many studies choose to analyze and classify count variables as binary. The purpose of this research is to determine how several predictor variables and a response variable relationship to each other's. To achieve this, logistic and Poisson regression models were being used. An overview of the count data related to postoperative nursing care quality among patients undergoing laparoscopic cholecystectomy in Erbil, Iraqi Kurdistan Region, is the main focus of this research. Used these two statistical tools to analysis the data of (150 nurses) collected from October -2023 to February-2024, who were working in surgical wards from hospitals, where data including gender (male, female) as a categorical response variable and with some predictor variables. To assess each model's goodness of fit, two criterions were used. The results indicated that the logistic regression model provided the best fit for modeling the binary response variable derived from count data, as it yielded lower values for both the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) compared to the alternative models. Microsoft Excel, Stata 16, and SPSS 25 are the statistical application software used.

Keywords: logistic regression, Poisson regression model, model selection criteria.

تقييم نموذج الانحدار اللوجستي ونموذج بواسون لتحليل بيانات جودة الرعاية التمريضية للمرضى الذين خضعوا لاستئصال المرارة بالمنظار في مدينة أربيل

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المستخلص. العديد من الدراسات تحليل وتصنيف متغيرات العد على أنها ثنائية. الغرض الرئيسي من هذا البحث هو تحديد كيفية ارتباط العديد من المتغيرات التنبؤ ومتغير الاستجابة ببعضها البعض. ولتحقيق ذلك، تم استخدام نماذج الانحدار اللوجستي ونموذج بواسون. إن مراجعة عدد البيانات لجودة رعاية التمريض بعد الجراحة للمرضى الذين خضعوا لاستئصال المرارة بالمنظار في أربيل، إقليم كردستان العراق هو المحور الرئيسي لهذا البحث. وقد استخدمت هاتان الأداتان الإحصائيتان لتحليل بيانات (١٥٠ ممرضًا) تم جمعها من أكتوبر ٢٠٢٣ إلى فبراير ٢٠٢٤، والذين كانوا يعملون في أجنحة الجراحة من مستشفيات، حيث تضمنت البيانات الجنس (ذكر، أنثى) كمتغير استجابة فئوي ومع بعض متغيرات التنبؤ. لتقييم مدى ملاءمة كل نموذج، تم استخدام معيارين. أظهرت النتائج أن نموذج الانحدار اللوجستي هو الأنسب لنمذجة متغير الاستجابة الثنائية في شكل بيانات العد بناءً على معياري التقييم المستخدمين معايير معلومات أكايكي (AIC) ومعايير المعلومات البايزية (BIC) تم استخدام برامج Microsoft Excel و Stata 16 و SPSS 25 كبرامج إحصائية تطبيقية.

الكلمات المفتاحية: الانحدار اللوجستي، نموذج الانحدار بواسون، معايير اختيار النموذج.

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Introduction

Regression analysis is a statistical methodology that examines the relationship between two or more quantitative variables, where one variable (the response) is predicted based on one or more explanatory variables. This approach is widely applied across various fields, including commercial, social, behavioral, and biological sciences. Regression may be of two types: linear and nonlinear. Simple and multiple linear regression are the different types of linear regression Cox and Donnelly, 2011), while quadratic, log-linear, exponential, cubic, logistic, Poisson, and power regression are nonlinear regressions. Notably, Poisson and Logistic regression are of interest for us in this research. Statistical methods with the many variables are commonly used in general health science literature. In the literature, the terms "multivariate analysis" and "multivariable analysis" are often used interchangeably. The relationship between two or more predictor (independent) variables and one outcome (dependent) variable is explored using multivariable methods. The outcome variable's predicted value is represented by the relationship model as a sum of products, each of which is generated by multiplying the independent variable's value by its coefficient (Park, 2013).

In many studies, research focuses on models in which the response variable is categorical. Considering that a number of the conditions for this technique's assumptions will not be met, we could not perform a multiple linear regression in this situation. We would instead perform a logistic regression analysis. Logistic regression may thus be seen as a method similar to multiple linear regression that also takes into consideration the categorical nature of the response variable. The logistic regression framework may be used to examine a response structure that has an outcome variable and a set of explanatory variables (one or more). There are so many ways in which proportions and probabilities differ from continuous variables. Proportions are restricted to values between 0 and 1, whereas continuous variables may, in principle, take any value from negative to positive infinity. Consequently, it is inappropriate to assume that proportions follow a normal distribution. Instead, proportions are more accurately modeled using a binomial distribution. Unlike the normal distribution, in which the mean and variance are independent, the binomial distribution has a variance that depends on its mean (Park, 2013).

When the outcome is a count, Poisson regression is useful. Similarly, Logistic regression is commonly used to estimate odds ratios when comparing different exposure groups, while Poisson regression is applied to estimate rates or counts across such groups. Both logistic and Poisson regression models are valuable tools for identifying the most influential variables and determining the direction and magnitude of each variable's effect. These models enable researchers to analyze relationships between dependent and independent variables while appropriately accounting for the structure of the observed data (Armstrong, 2012), (Ijomah, et al., 2018).

multiple regression models and Logistic regression are similar to the general poisson regression model. The Poisson distribution has many keeping count applications, include: 1) Telecommunication, 2) Biology, 3) Radioactivity, etc. Similar to the previous example, a model of

logistic regression is an essential model to take account when a response variable has two possible outcomes, such as the financial performance of the company (loss or profit), blood pressure, etc. For the analysis of data from either observational or experimental investigations, both models are suitable (Michael et al, 2005). Given that the response results are discrete (or binary response variables), Poisson and Logistic Regression models were taken into consideration in this article (Ijomah et al., 2018).

1st: Theoretical side

1- Logistic Regression Modeling for Binary Response Variable

Logistic regression is primarily used to model a binary outcome variable as a function of one or more explanatory variables, known as predictors. The binary outcome is commonly referred to as the response variable or dependent variable; in this study, the term "response variable" is used, as it is the preferred and widely accepted terminology in modern statistical literature. For the model to adequately fit the data, certain underlying assumptions must be satisfied (Hilbe, 2015):

- The predictor variables are assumed to be independent of one another, with no strong correlation between them.
- The predictor variables are assumed to have a statistically significant association with the response variable.
- the observations or data elements of a model are also uncorrelated.

I have emphasized that binary response logistic regression is based on the Bernoulli probability distribution, which consists of a distribution of (1 and 0). The probability function can be expressed for a random sample as:

$$f(y;p)\prod_{i=1}^{n} p_i^{y_i}(1-p_i)^{1-y_i} \qquad (1)$$

In this context, the joint probability density function (PDF) is expressed as the product (Π) of the individual probability density functions for each observation in the dataset, where each observation is indexed by the subscript (i). then characterize The Bernoulli distribution for a single observation is defined as follows:

$$f(y_i;p_i) = p_i^{y_i}(1-p_i)^{1-y_i} \qquad (2)$$

Logistic regression is a statistical modeling technique used to describe the relationship between one or more predictor variables and a categorical response variable. It is particularly appropriate when the response variable has two possible outcomes. Also known as the logistic or logit model, logistic regression examines the influence of multiple independent variables on a categorical dependent variable and estimates the probability of an event occurring by fitting the data to a logistic function. Logistic regression models are commonly classified into two types: binary logistic regression and multinomial logistic regression. Binary logistic regression is applied when the dependent variable is dichotomous, while the independent variables may be either continuous or categorical (Park, 2013). Examples of binary response variables include outcomes such as passing or failing an examination, answering yes or no to a survey question, and having either high or low blood pressure. To illustrate the contrast with continuous outcomes, consider the simple linear regression model:

$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$, $Y_i = 0,1$ (3)

Where the outcome variable Y_i is binary, taking values of either 0 or 1. Consequently, the expected value $E(Y_i)$ represents the probability that the event of interest occurs for the i-th observation. Since $E(\varepsilon_i)$, it follows that:

$E(Y_i) = \beta_0 + \beta_i X_i$ (4)

Consider (Y_i) to be a discrete random variable for which we can state the probability distribution as follows:

Y_i	Probability
1	$P(Y_i = 1) = p_i$
0	$P(Y_i = 0) = 1 - p_i$

Thus, p_i is the probability when $(Y_i = 1)$ and $(1 - p_i)$ is the probability that $(Y_i = 0)$. With the logistic model, estimates of π_i from equations like the one above will always be between 0 and 1. By definition of expected value of a random variable in equation (4), we obtain

$$E(Y_i) = 1(p_i) + 0(1 - p_i) = p_i = P(Y_i = 1) \qquad (5)$$

Equalling equation (4) and (5). we thus have

$$E(Y_i) = \beta_0 + \beta_i X_i = p_i \qquad (6)$$

Then, the logistic mean response function is:

$$E(Y_i) = p_i = \frac{\exp(\beta_0+\beta_i X_i)}{1+\exp(\beta_0+\beta_1 X_i)} \qquad (7)$$

2- Logistic Regression Parameter Estimation Using Maximum Likelihood

Let the discrete random variable Y_i be Bernoulli random variable and each Y_i observation is an ordinary Bernoulli random variable where:

$$\left.\begin{matrix} P(Y_i = 1) = p_i \\ P(Y_i = 0) = 1 - p_i \end{matrix}\right\} \qquad (8)$$

Then, its probability distribution is representing as follows:

$$f_i(Y_i) = p_i^{Y_i}(1 - p_i)^{1-Y_i} \quad , \quad Y_i = 0,1 \quad , \quad i = 1,2,3, \dots, n \qquad (9)$$

Note that $f_i(1) = p_i$ and $f_i(0) = 1 - p_i$

hence, $f_i(Y_i)$ simply represents the probability that, since the Y_i observation are independent. Their joint probability function is:

$$L(Y_1, Y_2, \dots, Y_n) = \prod_{i=1}^{n} f_i(Y_i) = \prod_{i=1}^{n} p_i^{Y_i}(1 - p_i)^{1-Y_i} \qquad (10)$$

Taking logarithm of equation (10), then the joint probability function:

$$log_e L(Y_1, Y_2, \dots, Y_n) = log_e \prod_{i=1}^{n} p_i^{Y_i}(1 - p_i)^{1-Y_i}$$

$$= \sum_{i=1}^{n} \left[Y_i log_e \left(\frac{p_i}{1 - p_i} \right) \right] + \sum_{i=1}^{n} log_e(1 - p_i) \qquad (11)$$

Since $E(Y_i) = p_i$ for a binary variable, it follows from equation (7) that:

$$1 - p_i = [1 + \exp(\beta_0+\beta_1 X_i)]^{-1} \qquad (12)$$

From equation (7), we obtain

$$log_e \left(\frac{p_i}{1 - p_i} \right) = \beta_0 + \beta_1 X_i \qquad (13)$$

And equation (11) can be expressed as follows:

$$log_e L(\beta_0, \beta_1) = \sum_{i=1}^{n} Y_i[\beta_0 + \beta_1 X_i] - \sum_{i=1}^{n} log_e\left(1 + (\beta_0+\beta_1 X_i)\right) \qquad (14)$$

Where $L(\beta_0, \beta_1)$ replaces $L(Y_1, Y_2, \dots, Y_n)$, This formulation explicitly expresses the function as the likelihood function of the parameters to be estimated, conditional on the observed sample data (Ijomah et al. ,2018).

In a simple logistic regression model, the maximum likelihood estimates of $\hat{\beta}_0$ and $\hat{\beta}_1$ are the values of β_0 and β_1 that maximize the log-likelihood function given in Equation (15). Because this maximization does not have a closed-form solution, iterative numerical optimization methods are required to obtain the estimates. Once the maximum likelihood estimates of $\hat{\beta}_0$ and $\hat{\beta}_1$ have been determined, they are substituted into the response function shown in Equation (7) to derive the fitted response function. The fitted probability for the i^{th} case or observation is denoted by $\hat{p}_i$.

$$\hat{p}_i = \frac{\exp(\hat{\beta}_0 + \hat{\beta}_1 X_i)}{1 + \exp(b_0 + b_1 X_i)} \qquad (15)$$

The fitted logistic response function is as follow:

$$\hat{p}_i = \frac{\exp(\hat{\beta}_0 + \hat{\beta}_1 X_i)}{1 + \exp(b_0 + b_1 X_i)} \qquad (16)$$

In practice, multiple logistic regression models typically include several predictor variables in order to achieve an adequate description of the data and to produce reliable predictions. In extending the simple logistic regression model, we simply replace $\beta_0 + \beta_1 X_i$ in Equation by $\beta_0 + \beta_1 X_i + \beta_2 X_2 + \cdots + \beta_k X_k$. To simplify the formula, we use matrix notation and the following three vectors:

$X'\beta = \beta_0 + \beta_1 X_i + \beta_2 X_2 + \cdots + \beta_k X_k \qquad (17)$

From equation (17) the simple logistic function (7) extends to the multiple logistic response function as follows:

$$E(Y) = \frac{\exp(X'\beta)}{1 + \exp(X'\beta)} \qquad (18)$$

3- Poisson Regression model with Binary Response Variable

Poisson regression is commonly used for the analysis of count data, which represent the number of times an event occurs within a specified period. Such data consist of non-negative integer values only (Karazsia et al, 2008). Accordingly, Poisson regression is formulated as a generalized linear model that employs a logarithmic link function to relate the expected count to the explanatory variable (Durrant, 2016). The Poisson distribution from the discrete distribution family can be expressed to represent variables with such asymmetric right-slope distributions (Moksony and Hegedus, 2014). Let x_i and y_i be observations from a data set. Here, the numbers xi and yi are respectively a vector of independent and dependent variables. Poisson regression analysis assumes that the y_i shows the Poisson distribution. The probability density function for the Poisson distribution with the parameter λ_i is given in the following formula;

$$f(y_i|x_i) = \frac{\lambda_i^{y_i} e^{-\lambda_i}}{y_i!} \quad , \quad y_i = 0, 1, 2, \ldots \qquad \ldots (19)$$

Let y_i denote the number of events observed, and let λ_i represent the rate of occurrence per unit of time. In this context, λ_i corresponds to the mean of the Poisson distribution, and the probability of observing a given count depends on the value of λ_i. The Poisson distribution is typically right-skewed, although it approaches a normal distribution as λ_i increases. A key characteristic of the Poisson regression model is that the mean and variance are equal. When this assumption is violated resulting in overdispersion or underdispersion the Poisson model may not adequately describe the data. In such cases, data transformation or the use of alternative modeling approaches may be necessary. The expected value and variance of y_i are given by:

$$\lambda_i = E(y_i|x_i) = Var(y_i|x_i) \qquad \ldots (20)$$

The link function, which defines the relationship between the expected value of the response variable and the independent variables, must take the specific form shown in Equation (21). This ensures that the expected value of y_i remains non-negative, as required for count data (Cameron and Trivedi, 1998).

$$\log(\lambda_i) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \ldots., \beta_k x_k \qquad \ldots(21)$$

In this equation, λ_i is an exponential function of the arguments. λ_i is the same as given in Equation below:

$$\lambda_i = \exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 \ldots., \beta_k x_k) = e^{x_i'\beta} \qquad \ldots(22)$$

Where β_0, $\beta_{1,..,k}$ represent the unknown parameters.

4- Poisson Regression Parameter Estimation Using Maximum Likelihood

There are several methods for estimating the regression coefficients β in Poisson regression, depending on the distributional properties of the dependent variable y_i. Maximum likelihood (MLE) method, artificial maximum likelihood (PMLE) method, and generalized linear models (GLM) are the most commonly applied and well-known of these techniques. The most used method for regression models is (Newton Raphson iteration) approach is typically employed in the likelihood method (MLE). The Poisson regression model's log likelihood function is as follows given an observation set:

$$L(\beta|(y,x)) = \sum_{i=1}^{n} P(y_i|\lambda_i) = \prod_{i=1}^{n} \frac{\lambda_i^{y_i} e^{-\lambda_i}}{y_i!} \qquad \ldots.(23)$$

When the logarithm of this function is taken, Equation below is obtained.

$$lnL(\beta) = \sum_{i=1}^{n} (y_i \ln(\lambda_i) - \lambda_i - lny_i!) \qquad \ldots(24)$$

Accordingly, the Poisson MLE of (β) value is calculated from the expression in Equation (25), (Durmuş and Güneri, 2020).

$$\sum_{i=1}^{n} (y_i - \lambda_i) x_i = 0 \qquad \ldots(25)$$

5- Wald statistic

The Wald statistic is used to evaluate the contribution of individual predictors and the significance of specific regression coefficients in a model. It is calculated as the square of the estimated coefficient divided by the square of its standard error. The Wald statistic tests the null hypothesis that the corresponding parameter β_j is equal to zero, indicating whether a predictor has a statistically significant effect on the response variable:

$$H_0: \beta_j = 0$$
$$H_1: \beta_j \neq 0$$

The Wald statistic is asymptotically distributed as a Chi-square distribution:

$$W_j = \frac{\beta_j^2}{SE_{\beta j}^2} \qquad (26)$$

Each Wald statistic is compared with a Chi-square with 1 degree of freedom. Wald statistics are easy to calculate but their reliability is questionable (Bewick et al., 2005).

2nd: Model Selection

The model selection criteria used in this study are the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Among the candidate models, the one with the smallest AIC and BIC values is considered the best-fitting model.

1- Akaike Information Criterion (AIC)

When comparing statistical models fitted using maximum likelihood (ML) to the same dataset, the Akaike Information Criterion (AIC) is used to evaluate the relative quality of each model. AIC not

only assesses the goodness of fit but also penalizes models with a larger number of predictors, thereby favoring more parsimonious models that achieve a balance between fit and complexity:

$$AIC = -2\ln(L) + 2P \quad \dots(27)$$

Where ln (L): In is the natural logarithm (Likelihood) is the value of the likelihood.
P: is the number of parameters in the model.
AIC can be calculated using residual sum of squares from regression (Henry, 2010):

$$AIC = n\ln(RSS/n) + 2P \quad \dots(28)$$

Where: n: is the number of data points (observations), RSS: is the residual sum of squares, The AIC values for a single model have no inherent meaning on their own. Their value becomes meaningful only when compared across competing models. Among the candidate models, the one with the lowest AIC is considered the best, as it achieves a balance between goodness of fit and model simplicity. By design, the AIC penalizes models with more parameters, discouraging overfitting and favoring models that explain the data well with fewer predictors (Adeti, 2016).

2- Bayesian Information Criterion (BIC)

The Bayesian Information Criterion (BIC) is another estimator used to assess the fit of models to a given dataset, particularly when the models being compared are non-nested. BIC not only evaluates how well a model fits the data but also includes a penalty for the number of parameters, favoring simpler models. Its computation is given by the following formula:

$$BIC = -2logL + klog\ n \quad \dots(29)$$

Where:
L: the maximum likelihood of the model
k: the number of parameters in the model
n: the number of observations (sample size)
Among competing models, the model with the smallest BIC value is considered the best-fitting model, as it achieves an optimal balance between goodness of fit and model complexity (Cameron and Trivedi, 2013).

3rd: Methodology

1- Study problem

Laparoscopic cholecystectomy is widely recognized as the gold standard treatment for gallstone disease. Despite its effectiveness, patients may experience postoperative complications, which can be minimized through the provision of high-quality nursing care and the application of evidence-based knowledge and practices by healthcare providers, particularly nurses in surgical wards. Therefore, this study aimed to investigate the effects of comfort nursing on postoperative quality of life, emotional well-being, and nursing satisfaction among patients undergoing laparoscopic surgery.

2- Importance of study

This article seeks to examine and compare the appropriateness and performance of logistic regression and Poisson regression models in analyzing factors that influence the quality of nursing care among patients undergoing laparoscopic cholecystectomy in Erbil City.

3- Study objectives

1. Identify the sociodemographic characteristics of nurses at teaching hospitals.
2. To assess post-operative nursing care quality in patients who underwent laparoscopic cholecystectomy in teaching hospitals.

4- Research population and sample

A cross-sectional descriptive study, non-probability (purposive sample) of (150) nurses, the study participants, who were nurses working in surgical wards, were selected from teaching hospitals, including Hawler Teaching Hospital, Rizgary Teaching Hospital, and Rojhalat Emergency Hospital,

and included both male and female staff. Data were collected using an observational checklist, which was divided into two sections. The first section gathered information on the socio-demographic characteristics of the participants and the second part is about the assessment of Postoperative nurses' care items consisting of five main domains. The data collected during the period of October -2023 to February-2024. The total data was (150), the data contains these variables (Age, Gender, Marital state, Level of education, …).

5- measures used and data collection methods in the study

Response variable Y: Gender (male and female), encoding in binary response for the criterion variable, in this case it will classify as: $Y = \begin{cases} 0 & \text{Female} \\ 1 & \text{Male} \end{cases}$

Table (1): explanation of total explanatory variables

	Explanatory variables
X_1	Age
X_2	Marital state
X_3	Level of education
X_4	The total number of years a nurse has worked in the surgical unit.
X_5	Making sure that the dressing remains clean, dry, and undamaged
X_6	Monitoring the surgical dressing and any drainage devices in place
X_7	Providing support to help the patient safely move out of bed and begin ambulation
X_8	Educating the patient and family to monitor and report any changes in stool color
X_9	Recording the rate, depth and sound
X_{10}	Placing the patient in a low Fowler's position to promote comfort and support respiratory function.
X_{11}	Helping patients begin walking early after surgery by providing support to the surgical incision site, particularly during coughing or movement, to reduce discomfort and prevent strain.
X_{12}	Performing gentle back massage to promote patient comfort and relaxation
X_{13}	Administering prescribed analgesic medications
X_{14}	Recording skin status and eye sclera
X_{15}	Caring of the drainage bag
X_{16}	Assess drain insertion site for signs of leakage, redness or signs of ooze
X_{17}	Check whether the surgical drain is securely fastened with sutures or tape, and document the findings.
X_{18}	Ensuring drain is located below the insertion site and free from kinds or knots
X_{19}	Recording fluid output while observing and reporting any alterations in urine color.
X_{20}	Encouraging soft diet after bowel sound return

4th: Practical side (Discussion)

This section is organized into two distinct parts; 1- Logistic regression and Poisson regression models that were fitted to the data. 2- This involves comparing the estimated parameters of the models and identifying the optimal model based on two evaluation criteria.

1- Fitting and Evaluation of Logistic and Poisson Regression Models

This section presents the regression coefficients for both the logistic regression and Poisson regression models, along with their standard errors and Wald test statistics for the associated parameters. There is important to put the hypothesis for both models:
H_0: The model provides a good fit to the observed data
H_1: The model does not fit the observed data well
We used the goodness of fit tests, if p-value of Wald test is less than accepted ($\propto = 0.05$) level, the test would reject the null hypothesis of an adequate fit, and if it is not then accepted the null hypothesis. illustrated the output of both models in table accordingly of the software used. As can be observed, some parameters' maximum likelihood coefficients are statistically significant at 5%;

statistically significant coefficients. The log-likelihood function (maximum likelihood estimators) of the Logistic regression is used to estimate the parameters denoted as $\beta_0, \beta_1, \ldots, \beta_6$. the response variable is (Gender), When the response variable is categorical, a common approach is to represent it using an indicator (or dummy) variable. In simple linear regression, we model the mean μ_y of the response variable (y) as a linear function of the explanatory variable (x_i): $\mu = \beta_0 + \beta_1 x_i$. Where y is just (male or female), the mean μ_y represents the probability (p) of one of the outcomes.

In Logistic regression model the mean (p) in terms of an explanatory variable (x_i). We might try to relate (p) and (x_i), as in simple linear regression: $p = \beta_0 + \beta_1 x_i$. Unfortunately, this is not a good model. Whenever $(\beta_1 \neq 0)$, extreme values of (x_i) will give values of $\beta_0 + \beta_1 x_i$ that fall outside the range of possible values of (p), $(0 \leq p \leq 1)$. The logistic regression solution to this difficulty is to transform the odds $(\frac{p}{1-p})$ using the natural logarithm.

We refer to this transformation as the log-odds or logit. In general, a statistical model is considered a simplified representation of a more complex reality. The fitted logistic regression function and the corresponding predicted values (i.e., estimates for the model parameters) presented in Table 2 can be expressed as follows;

$$\hat{p}_i = \frac{\exp\left(\hat{\beta}_0 + \hat{\beta}_3 X_3 + \hat{\beta}_7 X_7 + \hat{\beta}_8 X_8 + \hat{\beta}_9 X_9 + \hat{\beta}_{13} X_{13} + \hat{\beta}_{14} X_{14} + \hat{\beta}_{15} X_{15} + \hat{\beta}_{16} X_{16} + \hat{\beta}_{18} X_{18} + \hat{\beta}_{19} X_{19}\right)}{1 + \exp\left(\hat{\beta}_0 + \hat{\beta}_3 X_3 + \hat{\beta}_7 X_7 + \hat{\beta}_8 X_8 + \hat{\beta}_9 X_9 + \hat{\beta}_{13} X_{13} + \hat{\beta}_{14} X_{14} + \hat{\beta}_{15} X_{15} + \hat{\beta}_{16} X_{16} + \hat{\beta}_{18} X_{18} + \hat{\beta}_{19} X_{19}\right)} \quad \ldots (30)$$

$$\hat{p}_i = \frac{\exp\left(8.612 + 0.636 X_3 - 2.137 X_7 + 1.226 X_8 - 2.299 X_9 - 3.456 X_{13} - 1.773 X_{14} - 1.451 X_{15} + 1.082 X_{16} - 1.116 X_{18} - 1.749 X_{19}\right)}{1 + \exp\left(8.612 + 0.636 X_3 - 2.137 X_7 + 1.226 X_8 - 2.299 X_9 - 3.456 X_{13} - 1.773 X_{14} - 1.451 X_{15} + 1.082 X_{16} - 1.116 X_{18} - 1.749 X_{19}\right)}$$

Table (2): Estimated Parameters, Standard Errors, and Wald Test Statistic

	Logistic regression model					Poisson regression model				
	Coef.	**S.E.**	**Wald**	**Sig.**	**Exp(B)**	**Coef.**	**S.E.**	**Wald**	**Sig.**	**Exp(B)**
Cons.	8.612	3.413	6.366	.012	5495.9	.814	1.6220	.252	.616	2.256
X_1	.033	.025	1.657	.198	1.033	.014	.0129	1.149	.284	1.014
X_2	.263	.504	.272	.602	1.301	.105	.2683	.153	.696	1.111
X_3	.636	.325	3.842	.050	1.889	.216	.1861	1.344	.246	1.241
X_4	.035	.027	1.684	.194	1.036	.006	.0143	.157	.692	1.006
X_5	.917	.569	2.597	.107	2.501	.226	.2866	.623	.430	1.254
X_6	-.906	.561	2.605	.107	.404	-.173	.2998	.334	.563	.841
X_7	-2.137	.584	13.378	.000	.118	-.622	.2682	5.383	.020	.537
X_8	1.226	.494	6.161	.013	3.409	.369	.2662	1.924	.165	1.447
X_9	-2.299	.639	12.954	.000	.100	-.554	.2740	4.083	.043	.575
X_{10}	.691	.514	1.808	.179	1.995	.233	.2669	.760	.383	1.262
X_{11}	.516	.473	1.190	.275	1.676	.039	.2600	.023	.880	1.040
X_{12}	.648	.562	1.329	.249	1.911	.130	.2854	.209	.648	1.139
X_{13}	-3.456	.769	20.197	.000	.032	-.883	.3107	8.068	.005	.414
X_{14}	-1.773	.559	10.065	.002	.170	-.541	.2629	4.235	.040	.582
X_{15}	-1.451	.586	6.133	.013	.234	-.358	.2901	1.526	.217	.699
X_{16}	1.082	.553	3.826	.050	2.952	.335	.3053	1.202	.273	1.398
X_{17}	.856	.515	2.759	.097	2.354	.331	.2674	1.529	.216	1.392
X_{18}	-1.116	.523	4.553	.033	.328	-.364	.2792	1.703	.192	.695
X_{19}	-1.749	.566	9.531	.002	.174	-.411	.2733	2.264	.132	.663
X_{20}	.976	.508	3.690	.055	2.654	.299	.2675	1.253	.263	1.349

From the results, it is seen that availability of $(X_3, X_7, X_8, X_9, X_{13}, X_{14}, X_{15}, X_{16}, X_{18}, X_{19})$ played major roles in logistic regression model, means that (X_3: Level of education, X_7: Providing support

to help the patient safely move out of bed and begin ambulation, X_8: Educating the patient and family to monitor and report any changes in stool color, X_9: Recording the rate, depth and sound, X_{13}: Administering prescribed analgesic medications, X_{14}: Recording skin status and eye sclera, X_{15}: Caring of the drainage bag, X_{16}: Assess drain insertion site for signs of leakage, redness or signs of ooze, X_{18}: Ensuring drain is located below the insertion site and free from kinds or knots, X_{19}: Recording fluid output while observing and reporting any alterations in urine color. The significance of the regression coefficients was assessed using the Wald Chi-square test. All coefficients, including the intercept, were statistically significant at the 5% level ($p < 0.05$). This suggests that the examined variables are key factors influencing the quality of nursing care provided to patients following laparoscopic cholecystectomy.

While (X_1:Age, X_2: Marital state, X_4: The total number of years a nurse has worked in the surgical unit, X_5: Making sure that the dressing remains clean, dry, and undamaged, X_6: Monitoring the surgical dressing and any drainage devices in place, X_{10}: Placing the patient in a low Fowler's position to promote comfort and support respiratory function, X_{11}: Helping patients begin walking early after surgery by providing support to the surgical incision site, particularly during coughing or movement, to reduce discomfort and prevent strain, X_{12}: Performing massage to the patient`s back, X_{17}: Check whether the surgical drain is securely fastened with sutures or tape, and document the findings, X_{20}:Encouraging soft diet after bowel sound return) of estimated coefficient are not significant because their p-values are greater than 5% level.

Considering for the Poisson regression, the log-likelihood function for Poisson regression to estimate the maximum likelihood estimators denoted as $(\beta_0,\beta_1,\dots,\beta_6)$ and it is obtained as in table (2), The Poisson Regression Model with significant parameters estimates as follows:

$$Ln\hat{\lambda} = 0.814 - 0.622X_7 - 0.554X_9 - 0.883X_{13} - 0.541X_{14} \quad \dots(31)$$

$$\hat{\lambda} = \exp(0.814 - 0.622X_7 - 0.554X_9 - 0.883X_{13} - 0.541X_{14}) \quad \dots(32)$$

Table above also shows that only four availability (X_7: Helping the patient to go out of bed, X_9: Recording the rate, depth and sound, X_{13}: Administering analgesics as prescribed, X_{14}: Recording skin status and eye sclera) have a main effect on the nursing care quality with significance (p-value < 0.05).

while ($X_1, X_2, X_4, X_5, X_6, X_{10}, X_{11}, X_{12}, X_{15}, X_{16}, X_{17}, X_{18}, X_{19}, X_{20}$) was seen not to have any effect, hence, insignificant.

2- Comparison and identification of the optimal model

In this part we present a table of model selection of two types of regression (logistic and poisson regression) models by criterions as well as some concepts that mentioned before, their values can be used for performing model selection based on comparison to models that fit the same data. the table supports the research as follows:

Table (3): Model selection by some criterions for both logistics and poisson regression models

	Logistic regression model	**Poisson regression model**
Number of observations	150	150
Pearson χ^2	77.836	68.874
AIC	249.704	261.524
BIC	312.927	324.747
Log likelihood	-103.852	-109.762
Variance function	$V(\lambda) = \lambda * (1 - \lambda)$	$V(\lambda) = \lambda$
Link function	$g(\lambda) = \log(\lambda/(1 - \lambda))$	$g(\lambda) = \log(\lambda)$

From the results of table (3) show the logistic regression model of their criterions have the lowest values Then, it can be seen that the value of, Pearson χ^2 and Log likelihood for logistic regression model equal to (77.836, -103.852) respectively. To assess the fit of the two models, model selection criteria such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion

(BIC) were used. The logistic regression model showed the lowest values of these criteria (AIC = 249.704, BIC = 312.927), indicating a better fit to the data. In contrast, the Poisson regression model yielded higher AIC and BIC values, suggesting a poorer fit. Therefore, for this dataset with a binary response variable, the logistic regression model is a more appropriate alternative to the Poisson regression model, as evidenced by its smaller criterion values and superior goodness of fit.

5th: Conclusion

In the last section we have studied the performance of each model, the last comparison reaches some conclusions that differ from the results:

1. The data of nursing care quality of patients with laparoscopic cholecystectomy is adequate depending on chi-square test.
2. The logistic regression model identified that these explanatory variables ($X_3, X_7, X_8, X_9, X_{13}, X_{14}, X_{15}, X_{16}, X_{18}, X_{19}$) are played major roles in logistic regression model (since, their coefficients are significant at 5% where p-value of them less than 0.05.
3. While the Poisson regression model also identified that had coefficient significant at5% with p-value of only four explanatory variables have values less than 0.05, which they are (X_7, X_9, X_{13}, X_{14}).
4. The four variable ($X_7, X_8, X_9, X_{13}, X_{14}$), which they are significant in both models X_7: Helping the patient to go out of bed, X_9: Recording the rate, depth and sound, X_{13}: Administering analgesics as prescribed, X_{14}: Recording skin status and eye sclera, they are much importance than other variables of nursing care quality of patients with laparoscopic cholecystectomy
5. The results indicate that the logistic regression model provides the best fit for modeling the binary response variable in the dataset. This conclusion is based on the two model evaluation criteria used: the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), for which the logistic regression model showed the most favorable values.

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