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Modeling Outpatient Visits Using Poisson and Negative Binomial Regression at Sarkies Aisiyiah Kudus Hospital

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ABSTRACT

Outpatient visits are an important indicator of healthcare service utilization and play a significant role in hospital service planning and resource management. This study aims to model the number of outpatient visits at Sarkies Aisiyiah Kudus Hospital using Poisson and Negative Binomial regression and to identify the factors influencing outpatient visits. This study used secondary data consisting of 41 daily observations from November 1 to December 12, 2025. The response variable was the daily number of outpatient visits, while the predictor variables were the number of BPJS patients, the number of operating clinics, and the number of doctors on duty. Data analysis was performed using RStudio. The results showed that all three predictor variables had a positive relationship with outpatient visits in the Poisson regression model. However, the overdispersion test produced a dispersion value of 10.04, indicating that the Poisson assumption of equidispersion was not satisfied. The Negative Binomial regression model showed that the number of BPJS patients and the number of clinics had a positive and significant effect on outpatient visits, while the number of doctors had a positive but non-significant effect. The Negative Binomial model provided a better fit, with an AIC of 435.58, compared with 673.48 for the Poisson model. Therefore, the Negative Binomial regression model was selected as the more appropriate model for outpatient visit data at Sarkies Aisiyiah Kudus Hospital.

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1. INTRODUCTION (10 PT)

Health services are an important aspect of improving the quality of life of the community. Hospitals, as healthcare facilities, play a strategic role in providing optimal services, particularly in outpatient care. The number of outpatient visits is often used as an indicator of healthcare utilization and the quality of services provided. A decline or fluctuation in the number of visits may indicate problems within the healthcare delivery system [1]. In addition, patient visit indicators are used to evaluate service effectiveness and support healthcare planning in healthcare facilities. The number of patient visits also serves as a basis for hospital management

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decision-making, including planning healthcare workforce requirements, providing service facilities, and evaluating service quality. Therefore, analyzing patient visit data plays an important role in supporting the effective management of healthcare services [2].

Outpatient visit data generally consist of discrete data representing the number of events occurring within a specific period (count data). Therefore, an appropriate statistical approach is a regression model for count data, such as Poisson regression. Poisson regression is widely used to model the number of events because it can identify factors that influence count data. It is considered an appropriate method for modeling event counts because it is consistent with the characteristics of count data [3]. Furthermore, this model is widely applied in the healthcare sector to analyze the number of disease cases and patient visits because of its ability to explain relationships among variables. According to Campbell (2021), the Generalized Linear Model (GLM) approach, particularly Poisson regression, is one of the most commonly used methods for analyzing count data because it can appropriately describe the relationship between a count response variable and predictor variables compared with linear regression [4].

However, in practice, overdispersion is frequently encountered, which occurs when the variance of the data is greater than its mean. This condition can make the Poisson regression model less appropriate. To address this issue, Negative Binomial regression can be used because it is more flexible in handling data with high variability [5]. Previous research has also shown that Negative Binomial regression can provide better results than Poisson regression for healthcare data characterized by overdispersion [6]. Violations of the Poisson assumption often occur due to overdispersion; therefore, alternative models such as the Poisson Inverse Gaussian or Negative Binomial regression may be required to improve model accuracy [3]. Similarly, Güneri and Durmuş (2021) reported that overdispersion occurs when the variance of the data exceeds its mean, making Negative Binomial regression more appropriate because it can produce more accurate parameter estimates than Poisson regression for overdispersed data [7].

In the context of healthcare services in Indonesia, several recent studies have indicated that patient visits tend to fluctuate, highlighting the need for appropriate analytical and predictive methods. For example, a study on predicting patient visits at community health centers (Puskesmas) showed that unstable visit patterns could affect the planning of medical personnel and healthcare facilities [8]. In addition, another study emphasized that patient visit analysis is important for supporting decision-making in healthcare service management [9]. Recent research has also demonstrated that statistical analysis of patient visit data can contribute to service optimization and more efficient allocation of healthcare resources. Yadav et al. (2021) further explained that selecting an appropriate statistical model for count data significantly affects the accuracy of analytical interpretations, thereby supporting more accurate decision-making in the healthcare sector [2].

Furthermore, research in Indonesia using Poisson and Negative Binomial regression approaches to analyze JKN patient visits demonstrated that these methods were effective in describing outpatient visit patterns and identifying the factors influencing them [10]. This finding indicates that the selection of an appropriate statistical model is essential for analyzing healthcare data. Other studies in applied statistics have also emphasized that regression-based modeling can improve prediction accuracy and support data-driven decision-making in the healthcare sector. In addition, Güneri and Durmuş (2021) demonstrated that the Negative Binomial regression model performs better when applied to count data affected by overdispersion, making it a suitable alternative for analyzing healthcare service data [7].

Sarkies Aisyiyah Kudus Hospital, as one of the healthcare facilities, has outpatient visit data that continue to develop each year. However, the patterns of these visits have not yet been optimally analyzed using an appropriate statistical approach. Such analysis is important to support service planning, resource management, and improvements in healthcare service quality. The optimal utilization of healthcare data analysis has also been recommended in various studies as a basis for strategic decision-making in hospitals. Considering that patient visit data are count data and may potentially exhibit overdispersion, an appropriate statistical model must be selected to ensure that the analysis provides valid information and supports the development of more effective healthcare service policies [2], [4].

Based on the above discussion, an appropriate analytical method is required to model outpatient visit data. Therefore, this study employs Poisson regression and Negative Binomial regression to determine the best-fitting model and identify the factors influencing the number of outpatient visits at Sarkies Aisyiyah Kudus Hospital.

2. RESEARCH METHOD

This study employed a quantitative approach using secondary data obtained from Sarkies Aisyiyah Kudus Hospital. The research was conducted through several stages, including problem identification, literature review, data collection, descriptive statistical analysis, model development, model comparison, and interpretation of results. The data consisted of 41 daily observations from November 1 to December 22, 2025, including the number of outpatient visits as the response variable and the number of BPJS patients, operating

clinics, and physicians on duty as predictor variables. Data were collected through documentation of hospital records and databases.

Data analysis was performed using RStudio with the readxl, stats, MASS, and AER packages. Descriptive statistics were initially used to describe the characteristics of the research variables. Subsequently, Poisson Regression was applied to model the number of outpatient visits. An overdispersion test was then conducted to determine whether the Poisson assumption was satisfied. When overdispersion was identified, Negative Binomial Regression was applied as an alternative model. The Poisson and Negative Binomial models were compared based on log-likelihood, Akaike Information Criterion (AIC), and deviance values. The model with a higher log-likelihood and lower AIC and deviance was considered the better-fitting model. Finally, the selected model was interpreted to identify the factors influencing the number of outpatient visits at Sarkies Aisiyiah Kudus Hospital.

3. RESULTS AND DISCUSSION

3.1. Descriptive Statistical Analysis

Table 1. Descriptive Statistics of Research Variables

Variable	Minimum	Q1	Median	Mean	Q3	Maximum
Outpatient Visits	77	179	213	221,6	256	405
BPJS Patients	0	107	162	149,6	190	301
Operating Clinics	4	10	12	11,46	13	16
Physicians on Duty	7	17	18	18,17	20	29

Based on Table 1, the number of outpatient visits during the study period ranged from 77 to 405 patients per day, with a mean of 221.6 patients and a median of 213 patients. The number of BPJS patients ranged from 0 to 301 patients, with a mean of 149.6 patients per day. Meanwhile, the number of operating clinics ranged from 4 to 16, with a mean of 11.46 clinics per day. The number of physicians on duty ranged from 7 to 29, with a mean of 18.17 physicians per day.

Overall, the descriptive results indicate considerable variation among the research variables. The response variable, outpatient visits, is count data consisting of non-negative integers, making Poisson Regression an appropriate initial modeling approach. However, the equidispersion assumption must first be evaluated. Therefore, Poisson Regression was subsequently performed, followed by an overdispersion test to determine whether Negative Binomial Regression was required.

3.2. Poisson Regression Analysis

Poisson Regression was used as the initial model to examine the relationship between the number of outpatient visits and the predictor variables, namely the number of BPJS patients, operating clinics, and physicians on duty. Parameter estimation was performed using the Maximum Likelihood Estimation (MLE) method with RStudio. The results of the Poisson Regression parameter estimation are presented in Table 2.

Table 2. Poisson Regression Parameter Estimates

Variable	Coefficient (Estimate)	Std. Error	p-value
Intercept	4.0412966	0.0343300	<0.001
BPJS Patients	0.0018269	0.0000967	<0.001
Operating Clinics	0.0657564	0.0057308	<0.001
Physicians on Duty	0.0159731	0.0033577	0.000002

3.2.1 Poisson Regression Model

Based on the parameter estimation results, the Poisson Regression model is:

$$\ln(\mu) = 4.0412966 + 0.0018269X_1 + 0.0657564X_2 + 0.0159731X_3$$

Where μ represents the expected number of outpatient visits, X_1 represents the number of BPJS patients, X_2 represents the number of operating clinics, and X_3 represents the number of physicians on duty. All regression coefficients are positive, indicating that increases in the number of BPJS patients, operating clinics, and physicians tend to increase the expected number of outpatient visits, assuming the other variables remain constant.

3.2.2 Simultaneous Significance Test

A Likelihood Ratio Test (LRT) based on analysis of deviance was used to examine whether all predictor variables jointly affected the number of outpatient visits. The analysis produced a p-value < 0.001, which is lower than the 0.05 significance level. Therefore, H_0 was rejected, indicating that the number of BPJS patients, operating clinics, and physicians on duty simultaneously had a significant effect on the number of outpatient visits.

3.2.3 Partial Significance Test

The Wald test was used to evaluate the effect of each predictor variable. The number of BPJS patients had a coefficient of 0.0018269 with $p < 0.001$, the number of operating clinics had a coefficient of 0.0657564 with $p < 0.001$, and the number of physicians on duty had a coefficient of 0.0159731 with $p = 0.000002$. Since all p-values were below 0.05, all three predictor variables had statistically significant effects on the number of outpatient visits.

3.2.4 Interpretation of Regression Coefficients

The regression coefficients were interpreted using the Incidence Rate Ratio (IRR), calculated as $IRR = e^\beta$.

Table 3. Incidence Rate Ratio (IRR) Values of the Poisson Regression Model

Variable	Coefficient (β)	IRR
BPJS Patients	0.0018269	1.0018
Operating Clinics	0.0657564	1.0680
Physicians on Duty	0.0159731	1.0161

An additional BPJS patient was associated with an estimated 0.18% increase in the average number of outpatient visits. An additional operating clinic was associated with an estimated 6.8% increase in outpatient visits, while an additional physician was associated with an estimated 1.6% increase. Among the three predictors, the number of operating clinics had the largest relative effect on outpatient visits.

3.3. Overdispersion

One of the important assumptions of Poisson Regression is equidispersion, where the mean and variance of the response variable are equal. When the variance is greater than the mean, the data are considered to exhibit overdispersion. In this condition, Poisson Regression may produce underestimated standard errors and potentially biased significance tests. Therefore, an alternative model, such as Negative Binomial Regression, is required.

In this study, overdispersion was assessed by comparing the Residual Deviance with the degrees of freedom. Based on the Poisson Regression results, the Residual Deviance was 371.4 with 37 degrees of freedom, resulting in a dispersion value of:

$$Dispersion = \frac{371.4}{37} = 10.04$$

Table 4. Overdispersion Test Results

Criterion	Value
Residual Deviance	371.4
Degrees of Freedom	37
Dispersion Value	10.04

The dispersion value of 10.04, which is substantially greater than 1, indicates that the outpatient visit data exhibit overdispersion. Thus, the equidispersion assumption of the Poisson Regression model is not satisfied.

Consequently, Poisson Regression is considered less appropriate for the data. Negative Binomial Regression was therefore used as an alternative because it incorporates an additional dispersion parameter, allowing it to accommodate variance greater than the mean. The Negative Binomial Regression model was subsequently applied to obtain a more appropriate model for the number of outpatient visits at RS Sarkies Aisyiyah Kudus.

3.4 Negative Binomial Regression Analysis

The overdispersion test of the Poisson Regression model showed that the outpatient visit data exhibited overdispersion, with a dispersion value of 10.04. Therefore, the analysis was continued using

Negative Binomial Regression, which can accommodate count data with variance greater than the mean. Parameter estimation was performed using the Maximum Likelihood Estimation (MLE) method with RStudio.

Table 5. Negative Binomial Regression Parameter Estimates

Variable	Coefficient (Estimate)	Std. Error	p-value
Intercept	3.8754505	0.2616408	<0.001
BPJS Patients	0.0015464	0.0004415	0.00046
Operating Clinics	0.0703905	0.0252580	0.00532
Physicians on Duty	0.0243532	0.0129320	0.05970

The results indicate that the coefficients for BPJS patients, operating clinics, and physicians on duty are positive. The number of BPJS patients and operating clinics had a statistically significant effect on outpatient visits ($p < 0.05$), whereas the number of physicians on duty did not show a statistically significant effect ($p = 0.05970$).

3.4.1 Negative Binomial Regression Model

Based on the parameter estimation results in Table 6., the Negative Binomial Regression model is expressed as follows:

$$\ln(\mu) = 3.8754505 + 0.0015464X_1 + 0.0703905X_2 + 0.0243532X_3$$

Where μ represents the expected number of outpatient visits, X_1 represents the number of BPJS patients, X_2 represents the number of operating clinics, and X_3 represents the number of physicians on duty.

The model indicates that the expected number of outpatient visits is associated with the number of BPJS patients, operating clinics, and physicians through a logarithmic link function. All regression coefficients are positive, indicating that an increase in each predictor variable tends to increase the expected number of outpatient visits, assuming the other variables remain constant.

3.4.2 Simultaneous Significance Test

The simultaneous significance test was conducted to determine whether the predictor variables jointly affect the number of outpatient visits. Based on the Likelihood Ratio Test (LRT) from the Negative Binomial Regression model, the resulting p-value was < 0.001 . Since the p-value is lower than the 0.05 significance level, the null hypothesis was rejected. Therefore, the number of BPJS patients, operating clinics, and physicians on duty simultaneously had a significant effect on the number of outpatient visits at RS Sarkies Aisyiah Kudus.

3.4.3 Partial Significance Test

The partial significance test was conducted using the Wald test to determine the individual effect of each predictor variable on the number of outpatient visits. The results showed that the number of BPJS patients had a regression coefficient of 0.0015464 with a p-value of 0.00046, indicating a significant effect on outpatient visits. The number of operating clinics had a coefficient of 0.0703905 with a p-value of 0.00532, also indicating a significant effect. Meanwhile, the number of physicians on duty had a coefficient of 0.0243532 with a p-value of 0.05970. Since the p-value was greater than 0.05, the number of physicians on duty did not have a statistically significant effect on outpatient visits at the 5% significance level. Although its coefficient was positive, there was insufficient statistical evidence to conclude that an increase in the number of physicians was associated with an increase in outpatient visits after controlling for the number of BPJS patients and operating clinics.

3.4.4 Interpretation of Regression Coefficients

Table 6. Incidence Rate Ratio (IRR) of the Negative Binomial Regression Model

Variable	Coefficient (β)	IRR = $\exp(\beta)$
BPJS Patients	0.0015464	1.0015
Operating Clinics	0.0703905	1.0730
Physicians on Duty	0.0243532	1.0247

The coefficients of the Negative Binomial Regression model were interpreted using the Incidence Rate Ratio (IRR), calculated by exponentiating the regression coefficients. The IRR indicates the expected change in the average number of outpatient visits for a one-unit increase in a predictor variable, assuming the other variables remain constant.

Based on Table 6, each additional BPJS patient is associated with an estimated 0.15% increase in the average number of outpatient visits. Each additional operating clinic is associated with an estimated 7.3% increase in outpatient visits. Meanwhile, each additional physician is associated with an estimated 2.5% increase; however, this effect is not statistically significant at the 5% significance level.

Overall, the Negative Binomial Regression results indicate that the number of BPJS patients and operating clinics significantly influence outpatient visits, while the number of physicians has a positive but statistically insignificant effect. The number of operating clinics has the largest IRR, indicating that it has the strongest relative association with the number of outpatient visits.

3.5 Comparison of Poisson and Negative Binomial Regression Models

After fitting the Poisson and Negative Binomial Regression models, the two models were compared to determine the most appropriate model for modeling the number of outpatient visits at RS Sarkies Aisyiyah Kudus. The comparison was based on several goodness-of-fit measures, including the Akaike Information Criterion (AIC), Residual Deviance, and Log-Likelihood. A model with a lower AIC and Residual Deviance and a higher Log-Likelihood value (closer to zero) is considered to have a better fit to the observed data.

3.5.1 Comparison of Akaike Information Criterion (AIC)

Table 7. Comparison of AIC Values

Model	AIC
Poisson Regression	673.48
Negative Binomial Regression	435.58

Based on Table 7, the Negative Binomial Regression model has an AIC of 435.58, which is substantially lower than the Poisson Regression model (673.48). Therefore, based on the AIC criterion, the Negative Binomial Regression model provides a better fit to the outpatient visit data than the Poisson Regression model.

3.5.2 Comparison of Residual Deviance

Table 8. Comparison of Residual Deviance Values

Model	Residual Deviance
Poisson Regression	371.40
Negative Binomial Regression	41.396

Based on Table 8, the Negative Binomial Regression model has a Residual Deviance of 41.396, substantially lower than the Poisson Regression model (371.40). This result indicates that the Negative Binomial Regression model provides a better fit to the outpatient visit data. The substantial reduction in Residual Deviance also indicates that the dispersion parameter in the Negative Binomial model effectively accommodates the overdispersion identified in the Poisson model.

3.5.3 Comparison of Log-Likelihood

Table 9. Comparison of Log-Likelihood Values

Model	Log-Likelihood
Poisson Regression	-332.74
Negative Binomial Regression	-212.79

Based on Table 9, the Negative Binomial Regression model has a Log-Likelihood value of -212.79, compared with -332.74 for the Poisson Regression model. Since the Negative Binomial Regression model has a higher Log-Likelihood value (closer to zero), it provides a better fit to the outpatient visit data than the Poisson Regression model.

3.5.4 Selection of the Best Model

The model comparison results indicate that the Negative Binomial Regression model outperformed the Poisson Regression model, as evidenced by its lower AIC and Residual Deviance values and higher Log-Likelihood value. Therefore, the Negative Binomial Regression model was selected as the best model for modeling the number of outpatient visits at RS Sarkies Aisyiyah Kudus.

This finding is consistent with the overdispersion test, which showed a dispersion value of 10.04, indicating that the equidispersion assumption of the Poisson Regression model was not satisfied. In contrast, the Negative Binomial Regression model can accommodate variance greater than the mean through an additional dispersion parameter, resulting in a better fit to the observed data.

Thus, Negative Binomial Regression was determined to be the most appropriate model for modeling outpatient visits at RS Sarkies Aisyiyah Kudus because it provides better goodness-of-fit measures and effectively addresses the overdispersion present in the data.

3.6 Discussion

The results of the analysis showed that the Negative Binomial Regression model was more appropriate for modeling the number of outpatient visits than the Poisson Regression model. This finding was based on the overdispersion test, which indicated that the data did not satisfy the equidispersion assumption of the Poisson Regression model. In addition, the parameter estimation results showed that the number of BPJS patients and the number of clinics had significant effects on the number of outpatient visits, whereas the number of physicians did not have a statistically significant effect at the 5% significance level.

Based on the Negative Binomial Regression results, the regression coefficient for the number of BPJS patients was 0.0015464, with a p-value < 0.05 . This result indicates that the number of BPJS patients had a significant effect on the number of outpatient visits at RS Sarkies Aisyiyah Kudus.

The positive regression coefficient indicates that an increase in the number of BPJS patients tends to be followed by an increase in the number of outpatient visits. Based on the Incidence Rate Ratio (IRR) of approximately 1.0015, each additional BPJS patient is estimated to increase the average number of outpatient visits by approximately 0.15%, assuming that the other variables remain constant.

Substantively, this finding indicates that the BPJS Health program contributes to increased utilization of healthcare services. Easier access to healthcare financing through BPJS allows people to obtain healthcare services without having to bear the entire cost independently. Consequently, the number of outpatient visits tends to increase as the number of BPJS patients increases.

This finding is consistent with the theory of healthcare utilization, which states that the availability of health insurance can improve people's access to healthcare facilities. In addition, this finding is also consistent with several previous studies showing that BPJS membership is associated with increased utilization of outpatient healthcare services.

The results of the analysis showed that the number of clinics had a regression coefficient of 0.0703905, with a p-value < 0.05 . Therefore, the number of clinics had a significant effect on the number of outpatient visits.

The positive coefficient indicates that the greater the number of operating clinics, the greater the number of outpatient visits. Based on the IRR of approximately 1.073, each additional clinic is estimated to increase the average number of outpatient visits by approximately 7.3%, assuming that the other variables remain constant.

This finding can be explained by the fact that an increase in the number of clinics expands the range of healthcare services available, thereby providing patients with more healthcare options. In addition, the addition of clinics increases the hospital's service capacity, allowing more patients to be served each day.

This finding supports the theory of healthcare service management, which states that service capacity is one of the factors influencing the number of patient visits. The more comprehensive the healthcare services available, the greater the potential for an increase in the number of patients utilizing these services.

Based on the Negative Binomial Regression results, the number of physicians had a regression coefficient of 0.0243532, with a p-value > 0.05 . Therefore, statistically, the number of physicians did not have a significant effect on the number of outpatient visit

Although the regression coefficient was positive, the statistical evidence in this study was insufficient to conclude that changes in the number of physicians directly affected the number of outpatient visits. This finding indicates that an increase in the number of physicians does not necessarily lead to an increase in the number of patients seeking treatment.

This condition may be attributed to several factors. The number of outpatient visits is influenced not only by the number of physicians available but also by other factors, such as the community's healthcare needs, physicians' practice schedules, the types of clinics available, the referral system, and BPJS membership. In addition, during the study period, the variation in the number of physicians was relatively limited, making its effect on the number of outpatient visits less apparent statistically.

Thus, although the number of physicians had a positive relationship with the number of outpatient visits, this effect was not statistically significant after accounting for the number of BPJS patients and the number of clinics in the model.

The overdispersion test showed that the Poisson Regression model produced a Residual Deviance of 371.40 with 37 degrees of freedom, resulting in a dispersion value of 10.04. This value was considerably greater than one, indicating that the outpatient visit data exhibited overdispersion.

The occurrence of overdispersion indicates that the variability in the number of outpatient visits was greater than that assumed by the Poisson distribution, which requires the mean and variance to be equal. This

condition may have been influenced by heterogeneity in patient characteristics, daily variations in the number of patient visits, changes in the number of operating clinics, and other hospital service-related factors that were not fully incorporated into the model.

If overdispersion is ignored, the standard errors estimated by the Poisson Regression model tend to be underestimated, thereby increasing the risk of errors in hypothesis testing. Therefore, Negative Binomial Regression is a more appropriate alternative because it includes a dispersion parameter capable of accommodating data variance that is greater than its mean.

The models were compared using three goodness-of-fit criteria: Akaike Information Criterion (AIC), Residual Deviance, and Log-Likelihood. Based on the analysis, the Negative Binomial Regression model had an AIC of 435.58, which was lower than the Poisson Regression model's AIC of 673.48. In addition, the Residual Deviance of the Negative Binomial Regression model was 41.396, which was substantially lower than the Poisson Regression model's value of 371.40. The Log-Likelihood of the Negative Binomial Regression model was also higher (i.e., closer to zero) than that of the Poisson Regression model.

These three indicators demonstrate that the Negative Binomial Regression model provided a better overall model fit than the Poisson Regression model. This finding indicates that the addition of a dispersion parameter in the Negative Binomial Regression model successfully addressed the overdispersion present in the outpatient visit data.

Therefore, the Negative Binomial Regression model was selected as the best model in this study because it was able to produce more stable parameter estimates and provide better goodness-of-fit measures. This finding is also consistent with the theory proposed by Cameron and Trivedi (2022), which states that for count data exhibiting overdispersion, Negative Binomial Regression generally provides a better fit than Poisson Regression. The finding is also consistent with Hilbe (2021), who explained that the dispersion parameter in Negative Binomial Regression allows the model to accommodate variance that exceeds the mean, thereby producing more reliable estimates.

4. CONCLUSION

Based on the results of the analysis, the Negative Binomial Regression model was more appropriate than the Poisson Regression model for modeling outpatient visits at RS Sarkies Aisyiyah Kudus. The Poisson model showed overdispersion, with a dispersion value of 10.04, indicating that the equidispersion assumption was not satisfied.

The Negative Binomial Regression results showed that the number of BPJS patients and the number of clinics had positive and significant effects on outpatient visits, while the number of physicians had a positive but non-significant effect at the 5% significance level. The Negative Binomial Regression model also provided a better goodness of fit, with a lower AIC (435.58), lower Residual Deviance (41.396), and higher Log-Likelihood (-425.576) than the Poisson model.

Therefore, Negative Binomial Regression was selected as the best model. The findings can support hospital management in planning outpatient service capacity. Future research may include additional factors to improve the model's ability to explain variations in outpatient visits.

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