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Application of gamma regression model for assessing factors affecting milk production in Holstein dairy herd

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ABSTRACT

Generalized linear models (GLMs) are an extension of the linear regression model which is a strong and flexible tool for generating relationships between predictors and response variable, GLMs are widely applied in different fields such as epidemiology, economy, finance, and veterinary medicine. Gamma regression is a type of generalized linear model that is used to model continuous response variables that are non-negative and have a skewed distribution. Reliable records of a commercial dairy farm in the Sharkia governorate of Egypt were used to collect data on 351 purebred Holstein-Friesian cows. These cows were delivered between January 2018 and December 2019. The purpose of this study was the application of gamma regression model for assessing factors affecting milk production in Holstein-Friesian dairy herd by evaluating several parameters such as calving season, parity, incidence of mastitis disease, days to first insemination (DFI), days in milk (DIM) and days open (DO). The study's findings showed that the winter and autumn calving seasons, the incidence of mastitis, and the number of days to first insemination (DFI) were significant factors for the 305-day milk yield; however parity, days open (DO), and days in milk (DIM) had little effect on the amount of milk produced by dairy farms.

1. INTRODUCTION

A prominent agricultural subsector in both developed and developing nations is the dairy sector. Cow's milk has recently been shown to be a rich source of protein, energy, and vital vitamins and minerals (German and Dillard, 2006). So, the desired goal for dairy herds was increasing both the quality and amount of milk they produce as well as improve reproductive efficiency (Senger, 2001). 305-day milk production is the benchmark on which culling and breeding decisions are frequently made. For a variety of reasons, a single test-day yield is rarely used to eliminate cows; in instance, low production on a specific test-day date may be the consequence of stress or accidents (Jemmali et al., 2004). Understanding the physiological and environmental elements that affect an animal's performance is crucial for increasing the productivity and profitability of dairy cows. One of the most important environmental elements influencing a cow's productivity and reproductive efficiency are herd, calving season herd, year of calving, and parity (Khosroshahi et al., 2011). To investigate milk yield and evaluate factors affecting milk production in dairy farms, gamma regression analysis was applied in this study. The 305-day milk production was predicted using either incomplete gamma function or linear regression models (Wood,1967). Gamma regression model (GRM) is a type of generalized linear models which is frequently used to model a skewed outcome variable that follows a gamma distribution with one or more explanatory variables. The medical sciences, economics, health care, veterinary medicine are just a few of the fields that use GRM (Amin et al., 2019). Unlike linear regression, which is based on the response variable has a normal distribution, gamma regression allows for the modeling of skewed distributions and can account for over-dispersion, and the variance is greater than the mean (Buckley, 2014). Gamma regression was demonstrated to be an effective technique for modeling over distributed count data in animal populations (Fieberg and Jenkins, 2005). Gamma distribution is a two-parameter family of probability distributions that is frequently used to model positive continuous data, including waiting times or sizes of organisms. Gamma regression has gained popularity in the context of big data and machine learning in recent years. For example, Chen et al. (2020) proposed a Bayesian approach to gamma regression that accounts for model uncertainty. Thus, this study aimed to use GRM to identify the variables that may affect milk production in Holstein-Friesian dairy herds, including calving season, parity, incidence of mastitis, days to first insemination (DFI), days open (DO), and days in milk (DIM).

2. MATERIALS AND METHODS

Herd management

At the dairy farm, each animal was housed in a free-stall barn with water splashing systems that served as cooling devices when the outside temperature rose above 30 °C. Three times a day, the cows were machine-milked, and each time, the yield and composition of the milk were recorded. According to the recommendation of Animal Production Research Institute (APRI), balanced total mixed rations which met all of the animals' needs, including those for maintenance and milk production, were supplied to them. Every animal received routine vaccinations against most frequent diseases

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such as hemorrhagic septicemia, brucellosis, and foot and had their mastitis vaccinations 30 days prior to calving for dry cows, and every 4 months for lactating cows. AfiFarm version 4.1, a commercial on-farm software package, tracked the reproductive and productive data.

Sampling and data collection

For research purposes, a standardized dataset of 351 purebred Holstein-Friesian cows was collected from reliable records of commercial dairy farms in the Sharkia governorate of Egypt in the period between January 2018 and December 2019. Throughout the year, all of the animals were kept in open systems with uncovered sheds, helped in the summer with a cool spraying system. The animals were fed on total mixed ration (TMR), which was divided into four different groups based on dry matter intake (DMI): pre-freshening freshly calved, low producing, and high producing cows. The data included 305-day milk yield (kg), calving season, parity, incidence of mastitis, days to first insemination , days open , and days in milk. The dependent variable was 305-day milk yield. However, the explanatory (predictor) variables included parity, calving season, incidence of mastitis, days open (DO) days to first insemination (days), and days in milk (DIM), (Table 1).

Ethical approval:

Each examination was performed using the approval number provided by Benha University's Ethics Committee: BUFVTM06-12-23.

Model Structure and Specification

Gamma regression model (GRM) is used to determine factors that affecting 305-day milk production, the equation of gamma regression according to Bossio and Cuervo (2015) is:

$$f(y_i) = \frac{1}{y\Gamma(\alpha)}\left(\frac{\alpha y}{\mu}\right)^{\alpha} e^{-\alpha y_i/\mu} I_{(0,\infty)}(y_i) \qquad (1)$$

Where:

$\mu, \alpha > 0, \Gamma(.)$: Denotes the gamma function,

$I(.)$: Is the indicator function.

$y_i \sim G(\mu, \alpha)$: Is used to denote that y (305-day milk yield) follows gamma probability distribution with $\mathrm{E}(y_i) = \mu$ and α defined as a shape parameter.

Evaluating the Parameters of the Model

For estimating generalized linear models, the maximum likelihood (ML) estimation technique is applied. To find estimates for population parameter values (e.g., estimates of standard errors, the slopes, etc.) that maximize the likelihood that the sample data originated from a population with these parameter values, maximum likelihood estimation was applied (Coxe ,Aiken, and West, 2013). The attractive qualities of maximum likelihood estimation (MLE) make it starting point for estimating the parameters of any distribution .Also, it is the most often used estimation approach in statistical inference, since its underlying motivation is simple and intuitive (Dey et al.,2019). The equation of likelihood function can be written according to Cepeda-Cuervo (2001) as follows:

$$L(\beta,\gamma) = \prod_{i=1}^{n} \frac{1}{\Gamma(\alpha_i)}\left(\frac{\alpha_i}{\mu_i}\right)^{\alpha_i} y_i^{\alpha_i - 1} \exp\left(-\frac{\alpha_i}{\mu_i} y_i\right) \qquad (2)$$

$$l(\beta,\gamma) = \sum_{i=1}^{n} \left\{-\log\left[\Gamma(\alpha_i)\right] + \alpha_i \log\left(\frac{\alpha_i y_i}{\mu_i}\right) - \log(y_i) - \left(\frac{\alpha_i}{\mu_i}\right) y_i\right\} \qquad (3)$$

Thus, assuming the regression structures defined by $\mu_i = x_i'\beta$, and $\alpha_i = z_i'\gamma$, the score statistics are given by:

$$\frac{\partial l}{\partial \beta_j} = \sum_{i=1}^{n} -\frac{\alpha_i}{\mu_i}\left(1 - \frac{y_i}{\mu_i}\right) x_{ij}, j = 1, \dots p \qquad (4)$$

$$\frac{\partial l}{\partial \gamma_k} = \sum_{i=1}^{n} -\alpha_i \left[\frac{d}{d\alpha_i}\log\Gamma(\alpha_i) - \log\left(\frac{\alpha_i y_i}{\mu_i}\right) - 1 + \frac{y_i}{\mu_i}\right] z_{ik}, k = 1, \dots, r \qquad (5)$$

and the Hessian matrix is determined by:

$$\frac{\partial^2 l}{\partial \beta_k \partial \beta_j} = \sum_{i=1}^{n} \frac{\alpha_i}{\mu_i^2}\left(1 - \frac{2y_i}{\mu_i}\right) x_{ij} x_{ik}, j, k = 1, \dots p \qquad (6)$$

$$\frac{\partial^2 l}{\partial \gamma_k \partial \gamma_j} = \sum_{i=1}^{n} -\alpha_i \left[\frac{d}{d\alpha_i}\log\Gamma(\alpha_i) - \log\left(\frac{\alpha_i y_i}{\mu_i}\right) - 1 + \frac{y_i}{\mu_i}\right] z_{ij} z_{ik} \qquad (7)$$
$$- \sum_{i=1}^{n} \alpha_i \left[\alpha_i \frac{d^2}{d\alpha_i^2}\Gamma(\alpha_i) - 1\right] z_{ij} z_{ik}, j, k = 1, \dots, r$$

The Fisher information matrix is given by:

$$-E\left(\frac{\partial^2 l}{\partial \beta_k \beta_j}\right) = \sum_{i=1}^{n} \frac{\alpha_i}{\mu_i^2} x_{ij} x_{ik}, j, k = 1, \cdots, p \qquad (8)$$

$$-E\left(\frac{\partial^2 l}{\partial \gamma_k \beta_j}\right) = 0, j = 1, \cdots, p, k = 1, \cdots, r \qquad (9)$$

$$-E\left(\frac{\partial^2 l}{\partial \beta_k \beta_j}\right) = \sum_{i=1}^{n} \alpha_i^2 \left[\frac{d^2}{d\alpha_i^2}\log\,\Gamma(\alpha_i) - \frac{1}{\alpha_i}\right] z_{ij} z_{ik}, j, k = 1, \cdots, r \qquad (10)$$

The diagonal block matrix corresponding to the shape regression parameter (γ) and the mean regression parameter (β) in the Fisher information matrix is clearly visible. Hence, β and γ are orthogonal (Cox and Reid ,1987). Finally, by taking into consideration the structure of the Fisher information matrix, Cepeda et al. (2001) show that the Fisher scoring information equation may be written as the following set of equations.:

$$\beta^{(k+1)} = \left(X' W_1^{(k)} X\right)^{-1} X' W_1^{(k)} Y \qquad (11)$$

$$\gamma^{(k+1)} = \left(Z' W_2^{(k)} Z\right)^{-1} X' W_2^{(k)} \tilde{Y} \qquad (12)$$

Where $\boldsymbol{W}_1^{(k)}$ is defined as a diagonal matrix with diagonal entries$w_{ii}^{(k)} = (\mu_i^2/\alpha_i)$, and

$$\tilde{y}_i = \eta_{2i} - \frac{1}{\alpha_i}\left[\frac{\partial^2}{\partial \alpha^2}\log\,\Gamma(\alpha_i) - \frac{1}{\alpha_i}\right]^{-1} \left[\frac{\partial}{\partial \alpha_i}\log\,\Gamma(\alpha_i) - \log\left(\frac{\alpha_i y_i}{\mu_i}\right) - 1 + \frac{y_i}{\mu_i}\right].$$

$\boldsymbol{W}_2^{(k)}$ Is known as diagonal matrix with diagonal entries $w_{ii}^{(k)} = 1/d_i$

$$d_i = \alpha_i^{-2}\left[\frac{d^2}{d\alpha_i^2}\log\,\Gamma(\alpha_i) - \frac{1}{\alpha_i}\right]^{-1}$$

3. RESULT

The results of table (1) showed summary statistics of mean and standard deviation for one dependent variable (305-day milk yield) and the three predictors of days open, days in milk, and days to first insemination

Table 1: Descriptive statistics for continuous variables used in gamma regression analysis:

Variables	Mean	Std. Deviation	Minimum	Maximum
Milk yield(day)	7154.0	1385.0	4658.0	10657.0
DO (days)	337.0	85.6	200.00	720.0
DIM (days)	65.0	23.0	35.0	224.0
DFI(days)	137.0	99.1	38.0	389.0

DO= days open, DIM= days in milk, DFI=days to first insemination.

As shown in table (2), the results of omnibus test showed that the LRχ^2 (likelihood ratio chi-square) value for the model with the log link function is 42.08 with 14 degrees of freedom and a p-value of 0.001. While, the relationship between 305-day milk yield and the predicted value of it was tested by Pearson correlation and the result showed significant correlation at the 0.01 level (Table 3).

Table 2: Goodness of fit by omnibus test in gamma Table 2: Goodness of fit by omnibus test in gamma regression analysis:

Chi-square	d.f	*P-value*
42.08	14	0.001***

***P< 0.001, chi-square value was highly significant.

Table 3: The association between milk yield and the predicted value by Pearson correlation analysis:

Variables	Number	Pearson correlation value	*P-value*
305-day milk yield	351	0.33**	0.001
Predicted value of mean of 305-day milk yield	351		

At *p-value* 0.001, the Correlation is significant.

The results of table (4) cleared the estimated coefficients from a gamma regression model with a log link function. In this specific table, the predictor variables included autumn calving season (Exp (B)=1.114, P-value= 0.001), winter calving season (Exp (B)=1.046, P-value= 0.03), Mastitis (Exp (B)=0.95, P-value= 0.04), parity=6, (Exp (B)=1.40, P-value= 0.04), and days to first insemination (Exp (B)=0.99, P-value= 0.001), were important explanatory factors for the amount of milk production. While, other calving seasons, cow parity, days in milk and days open were not significantly associated with the response variable at the 0.05 level of significance

Table 4: Factors affecting 305-day milk yield that analyzed by gamma regression analysis:

Variables	Estimate	SEM	*P-value*	EXP(B)	95% Confidence interval
Intercept	8.66	0.195	0.00	5759.2	[8.28, 9.04]
Season of calving	0.036	0.0347	0.30 NS	1.04	[-0.032, 0.104]
Summer vs Spring	0.108	0.0317	0.001**	1.11	[0.046, 0.170]
Autumn vs Spring	0.062	0.0294	0.03*	1.05	[0.004, 0.119]
Winter vs Spring					
Cow with mastitis vs without mastitis	0.035	0.019	0.04*	0.95	[-0.003, 0.074]
Parity	0.226	0.183	0.23 NS	1.25	[-0.133, 0.585]
Parity=1	0.231	0.182	0.21 NS	1.26	[-0.127, 0.589]
Parity=2	0.219	0.183	0.23 NS	1.25	[-0.140, 0.579]
Parity=3 Parity=4 Parity=5	0.243	0.185	0.19 NS	1.28	[-0.120, 0.606]
Parity=6 parity=7	0.194	0.188	0.30 NS	1.21	[-0.175, 0.563]
	0.338	0.195	0.08 NS	1.40	[-0.043, 0.719]
	0.001	0.209	0.99 NS	1.00	[-0.408, 0.409]
Days in milk	3.61E-5	0.001	0.76 NS	1.00	[0.001 , 0.002]
Days to first insemination	-0.002	0.005	0.001 **	0.99	[-0.002, -0.001]
Days open	-3.75E-5	0.001	0.21 NS	1.00	[0.001 , 0.002]

References were multiparous cow, and spring season.
** Highly significant at level (*P-value* ≤ 0.001). *Significant at level (*P-value*≤ 0.05). NS= Non-significant *(P-value* ≥ 0.05).
**Highly significant at level (P-value ≤ 0.001). *Significant at level (P-value≤ 0.05). NS= Non-significant (P-value ≥ 0.05).

4. DISCUSSION

This study aimed to assess the factors influencing 305-day milk yield in Holstein dairy herds depending on some environmental and reproductive factors such as calving season, incidence of mastitis, number of parities in dairy cows, (DO), (DFI) and (DIM). The study's findings demonstrated the effectiveness of the gamma regression model in identifying the relationship between significant explanatory variables and milk output. This result was in the same line with Congleton and Everett, (1980) who applied the Incomplete Gamma Function to for evaluating the 305-day milk production. The omnibus test which used to determine whether the model significantly explains the variability in the response variable confirmed that the model with the log link function significantly explains the variability in the outcome variable of 305-day milk yield. The result of this study agreed with the findings of Abo-Gamil et al. (2021), who confirmed that non-genetic factors must be taken into consideration when assessing the 305-day milk yield in Holstein Friesian cows.

Consistent with previous report of Abd-El Hamed and Kamel (2021), the present study revealed a strong correlation between the season of calving and the 305-day milk production. The incidence of 305-day milk yield over other seasons is significantly influenced by the autumn and winter calving seasons. The estimated EXP (B) for the autumn season equal 1.11 (more than 1), which indicated that cows calved in autumn season had 11% increase in the amount of milk production than those calved in spring season, while EXP (B) for winter season equal 1.05 (more than 1), which showed that cows calved in winter season had 5% increase in the amount of milk production than those calved in spring season. This result is in the same line with Abd-El Hamed and Kamel (2021) who noted that the winter season yields the highest milk yield in dairy cows, and it is in indirect opposing to Bolacali and Öztürk (2018) and Manzi et al. (2020) results that the calving season has no apparent effect on the 305-day milk yield. However, the findings conflicted with those of Abo-Gamil et al. (2021), who noted that dairy cows that gave birth in the spring produced more milk than they did in other seasons. This could be attributed to the year-round availability of grain and fodder.

Our results revealed that the cow with mastitis had significant effect on 305-day milk production (p-value=0.04), the estimated EXP (B) for cows with mastitis equal 0.95 (less than 1) which means that there was 5% decrease in 305-day milk yield in cows with mastitis than cows with no mastitis. This is in agreement with Harjanti and Sambodho (2020) who showed statistically negative correlation between the level of mammary inflammation and milk production in dairy cows.

It was found that cow parity didn't have significant effect on milk production in dairy herds (p-value > 0.05). The finding of a non-significant effect of parity conflicts with previous studies by Manzi et al. (2020) and Nguyen et al. (2023), which found that parity, had a substantial effect on milk production. Days in milk (DIM) have no effect on 305-day milk production. This is consistent with the findings of Abd-El Hamed and Kamel (2021), who reported that the 305-day milk yield values were reached at days in milk 301-330 days, after which the milk yield decreased. However, the results of Fouda et al. (2020) and Sevinc et al. (2020) contradicted this finding.

The current research found that the 305-day milk yield didn't have a significant effect on the reproductive indices as DO. Unlike this, DFI was a significant factor for 305-day milk yield with EXP (B) = 0.99 (less than 1) which explain that for every one point increase of DFI, we would expect that about 1% decrease in 305-day milk yield. This outcome was consistent with the findings of Eicker et al. (1996), who discovered that cows producing milk in the top percentile had a somewhat lower conception rate than those producing milk in the lowest quintile; in addition, Amma et al. (2024) found that reproductive performance and milk output are negatively correlated, there was a clear reduction in reproductive indices in parallel with an increase in milk production. López-Gatius et al. (2006), on the other hand, think that this negative association, if it exists at all, is not inevitable.

5. CONCLUSIONS

In this paper, we proposed the application of gamma regression model on veterinary data consists of 351 purebred Holstein-Friesian cows that were gathered from reputable records of big commercial dairy farms in Egypt, the data included some productive and reproductive measurements in order to determine factors influencing 305- day milk yield in Holstein dairy herds depending on these measurements. The result revealed that calving season, incidence of mastitis and DFI were significant factors for 305-day milk yield, while other factors of parity, DO, DIM didn't influence the 305-day milk yield.

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CONFLICT OF INTEREST

There is no conflict of interest.

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