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Determination of value at risk as the threshold for motor vehicle insurance claims using the gamma distribution

Ardiyan Budiman[1], Wahri Irawan[1], Mochamad Indrajit Roy[1]
[1] Department of Islamic Insurance, Faculty of Islamic Economics and Business,
Universitas Islam Negeri Sultan Maulana Hasanuddin Banten, Serang, Indonesia

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ABSTRACT

The growth of motor vehicles in Indonesia has increased the risk of traffic accident losses, highlighting the need for accurate claim risk management by insurance companies. One approach to determining claim thresholds is Value-at-Risk (VaR). This study aims to estimate VaR as a claim threshold for motor vehicle insurance by modeling claim amounts using the Gamma distribution. The research methodology includes descriptive analysis of claim data, distribution selection, parameter estimation via maximum likelihood, and goodness-of-fit testing with the Kolmogorov–Smirnov test. The data consist of 113 paid claim amounts from motor vehicle insurance during the 2024–2025 period. The results indicate that the claim data are positive and right-skewed, making them suitable for modeling with a Gamma distribution with shape parameter $\alpha = 10.9073$ and scale parameter $\theta = 0.5457$. The calculated VaR values are 30.8716 at the 95% confidence level and 36.687 respectively levels.

Corresponding Author:

Wahri Irawan
Universitas Islam Negeri Sultan Maulana Hasanuddin Banten, Serang, Indonesia
Email: wahri.irawan@uinbanten.ac.id

1. INTRODUCTION

The number of motor vehicles in Indonesia has continued to increase over time, reflecting the growing mobility needs of the population. Motor vehicles such as motorcycles, cars, and buses have become essential tools for daily activities and for travel. They play an important role in economic, social, and community development. This growth indicates society's increasing dependence on motorized transportation. As a result, transportation has become an inseparable part of modern life [1].

Along with the growing demand for transportation, the number of motor vehicles has increased significantly across various regions. This rapid increase has contributed to higher traffic density, especially in urban areas. Road infrastructure development often does not keep pace with the growth in vehicle numbers. Consequently, traffic congestion has become a common phenomenon in many cities. This situation creates challenges for traffic management and transportation systems [2].

This condition has led to increased traffic congestion and posed various risks. These risks include traffic accidents, vehicle damage, theft, and other potential hazards that may cause losses to road users. The higher the number of vehicles, the greater the probability of risk occurrences [3]. Such risks can result in both material and non-material losses. Therefore, the growth in motor vehicle usage is closely associated with increased exposure to transportation-related risks [4].

Therefore, measures to reduce or transfer these risks are necessary, one of which is through insurance. Insurance, or coverage, is defined as an agreement in which the insurer binds itself to the insured in exchange for the payment of a premium [5]. Under this agreement, the risk initially borne by individuals or organizations can be transferred to the insurance company. This mechanism provides protection against potential financial losses. As a result, insurance becomes an important instrument in managing various forms of risk [6].

The purpose of insurance is to provide compensation for losses, damages, or the loss of expected profits that may occur as a result of unforeseen events. This compensation mechanism helps individuals and institutions maintain financial stability when unexpected losses occur. Insurance, therefore, plays a strategic role in economic security [7]. It also supports long-term planning by reducing uncertainty. Consequently, insurance contributes significantly to social and economic resilience. Value at Risk (VaR) is one of the most widely used risk measures in the financial and insurance industries to estimate the maximum potential loss at a given confidence level over a specified time period [8].

The concept of VaR is one of the most widely used risk measures in the financial and insurance industries to estimate the maximum potential loss at a given confidence level over a specified time period. The concept of VaR provides information about the maximum potential loss and is readily applicable to risk management decision-making, including determining insurance claim limits. In motor vehicle insurance, VaR can be used to estimate the maximum claim amount that insurers can tolerate. This enables insurers to manage financial risk more effectively. Thus, VaR serves as an important analytical tool in insurance risk management [9].

VaR estimates are highly dependent on the accuracy of the probability distribution assumptions used in modeling claim data. In insurance practice, claim data is generally positive and right-skewed, meaning it has a long right tail. This is due to the possibility of very large claims occurring, even though they are relatively rare. According to risk theory, this phenomenon is known as heavy-tailed behavior, where a small number of extreme events can contribute significantly to total losses. This condition makes the choice of a probability distribution a crucial factor in risk measurement, as incorrect distributional assumptions can cause significant bias in VaR estimates, either underestimating or overestimating risk.

The estimation of VaR is highly dependent on the accuracy of the assumed probability distribution of claim data. Insurance claim data tend to be positive and are typically right-skewed [10].

Therefore, the Gamma distribution is often used to model insurance claim data more accurately. Theoretically, the Gamma distribution is included in continuous probability distributions defined in a positive domain, so mathematically it is suitable for modeling claim amounts that cannot be negative. In actuarial risk modeling theory, the Gamma distribution is known for its flexibility in modeling data distributions, ranging from exponential to normal, depending on the parameter values. This is in line with the concept of loss severity modeling, in which the distribution must realistically capture variations in loss severity [11].

Various studies have shown that the Gamma distribution is effective for loss risk analysis in insurance companies, based on historical claim data. In the framework of empirical risk modeling, the Gamma distribution often shows better goodness-of-fit than other distributions, such as normal or log-normal, for certain types of claim data. Theoretically, this is supported by the principles of statistical inference, where an appropriate distribution minimizes parameter estimation errors and improves the accuracy of risk predictions. Thus, the use of the Gamma distribution is not only practical, but also has a strong scientific basis in statistical and actuarial theory [12].

The main advantage of the Gamma distribution lies in the flexibility of its curve shape in capturing data characteristics. In probability distribution theory, this flexibility stems from the existence of two main parameters, namely the shape parameter (start equation theta), which allows for significant changes in the distribution's shape. This concept is in line with parametric modeling theory, where a good statistical model must have parameters that can adjust to the empirical data structure. In other words, the Gamma distribution is not rigid, but adaptive to various claim data distribution patterns [13].

In addition, the shape of the Gamma distribution curve is not only determined by the random variable itself, but is also greatly influenced by variations in its parameters. From a statistical distribution theory perspective, small changes in the shape and scale parameters can result in large changes in skewness, kurtosis, and data dispersion [14]. This is relevant to risk sensitivity theory, where the sensitivity of a model to changes in parameters is an important indicator of risk. With this capability, the Gamma distribution is particularly well suited to financial and actuarial risk modeling, especially for measuring extreme risk, such as VaR [15].

The use of the Gamma distribution in VaR calculations enables insurance companies to obtain more accurate risk estimates compared to the normal distribution approach, which is less suitable for modeling insurance claim data [16]. Accurate estimates of distribution parameters can yield VaR values that reflect the actual risk conditions of the motor vehicle insurance portfolio. This is essential to ensure that the established claim thresholds are neither too low, which could harm the company, nor too high, which could potentially place excessive financial strain on the company [17].

This study aims to determine the VaR as the claim threshold in motor vehicle insurance through claim modeling using the Gamma distribution. This approach is used to obtain a more accurate and representative estimate of loss risk that reflects the characteristics of claim data, which are positive, asymmetric, and right-skewed. By using the Gamma distribution as a probabilistic model, this study seeks to develop a quantitative framework that more realistically captures risk patterns than conventional distributions, which are less well-suited to the characteristics of insurance claim data.

In addition, the VaR estimates produced in this study serve not only as a statistical measure of risk but also as a strategic instrument for risk management decision-making at insurance companies. VaR, as a claim threshold, can serve as a basis for formulating underwriting policies, determining claim reserves, setting premiums, and planning for solvency and capital adequacy. Thus, this study integrates a quantitative statistical approach with practical needs in insurance risk management.

The novelty of this study lies in the specific application of the Gamma distribution in determining VaR as the claim threshold for motor vehicle insurance. Unlike previous studies, which generally use VaR only as a measure of portfolio or financial risk, this study positions VaR as an operational instrument for insurance claims, specifically to determine the high-risk claim threshold. The integration of the Gamma distribution model and the concept of VaR in the context of motor vehicle insurance makes a methodological contribution to the development of a claim data-based risk management model.

2. METHOD

This study was conducted through several systematic stages to determine the loss risk analysis model, namely:

1. Descriptive Analysis

   This stage is conducted to identify the characteristics of the data distribution and determine the most representative distribution type. The analysis focuses on the shape of the distribution and the properties of its tail behavior. A distribution is classified as right-skewed if the skewness value is greater than zero and is considered to exhibit a heavy tail if the mean excess function increases linearly.
2. Selection of Distribution Type

   To ensure the model's validity, this study selected the probability distribution that best fit the empirical data. This determination was made through a visual approach using a Quantile-Quantile Plot (QQ Plot). The QQ Plot was used to compare the sample quantiles with the theoretical quantiles of the distribution under consideration.
3. Parameter Estimation

   This stage involves estimating the model parameters using Maximum Likelihood Estimation (MLE).
4. Mode *Goodness of Fit*

   This stage evaluates the accuracy of the fitted distribution using the Kolmogorov–Smirnov statistical test.

3. RESULTS AND DISCUSSION

The data used in this study consists of paid-amount claim data obtained from the insurance company XYZ. The claim data were collected over the period 2024–2025 and comprise 113 claim amounts with values greater than zero. This dataset represents actual claim payments and serves as the empirical basis for the analysis. The data provide a real representation of claim behavior within the observed period.

In this study, a standardization process was applied by dividing each data value by 1,000,000. This transformation was conducted to simplify the numerical scale and facilitate statistical analysis and interpretation. Standardization also helps improve computational efficiency and readability of results. Through this process, the data becomes more manageable for modeling and analysis purposes.

Table 1 provides the descriptive statistical results of the paid amount data, while Figure 1 presents a histogram illustrating its distribution. These descriptive statistics provide an overview of the data's central tendency and variability. The histogram visually represents the distribution pattern and overall shape of the data. Together, Table 1 and Figure 1 support the initial exploration and understanding of the dataset. Presents a histogram of the paid amount data.

Table 1. Descriptive Statistics of Paid Amount Data (Adjusted)

N	Mean	Sd	Median	Min	Max	Range	Skew	Kurtosis
113	19.99	6.25	18.35	9	36.54	27.54	0.77	0.03

Based on Table 1, the mean of 19.99 and the median of 18.35 indicate a difference in the measure of data centralization. This difference indicates that the data distribution is not symmetrical. This indicates that the data is not evenly distributed around the median. Thus, the data distribution shows an imbalance in the values.

In addition, the skewness value ($0.77 > 0$) indicates that the data are right-skewed. This means that most of the data is concentrated at relatively small values, while a small portion is at larger values on the right side of the distribution. This distribution pattern indicates a longer right tail. This further reinforces the conclusion that the data distribution is asymmetrical.

This characteristic is consistent with the nature of the Gamma distribution, which is commonly used to model right-skewed, positive-valued data, such as claim amounts. Therefore, the Gamma distribution is considered appropriate for modeling the data in this study. Before performing the fitting process using the Gamma distribution, it is necessary to first determine the most appropriate estimate of the Gamma distribution parameters based on the available data using R Studio statistical software version 4.5.1. With this step, the model built is expected to represent the data pattern more accurately.

Table 2. Estimated Parameters of the Gamma Distribution Based on Motor Vehicle Insurance Claim Paid Amount

Distribution	Parameter	Estimated Parameter
Gamma Distribution	α θ	10,9072708 0,5457448

Furthermore, a histogram of the motor vehicle insurance claim paid amounts and the probability density function graph of the Gamma distribution based on the estimated parameters will be presented Table 2.

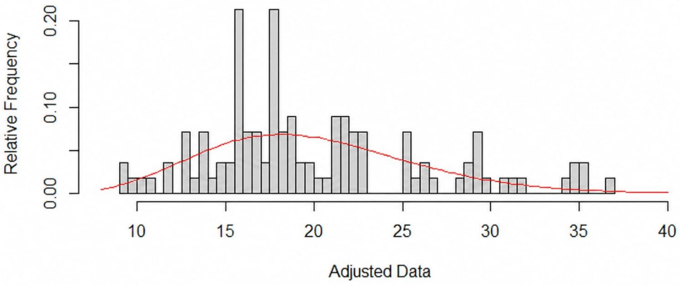

Figure 1. Histogram of Claim Amount Data and the Probability Density Function of the Gamma Distribution ($\alpha = 10{,}9072708$, $\theta = 0{,}5457448$)

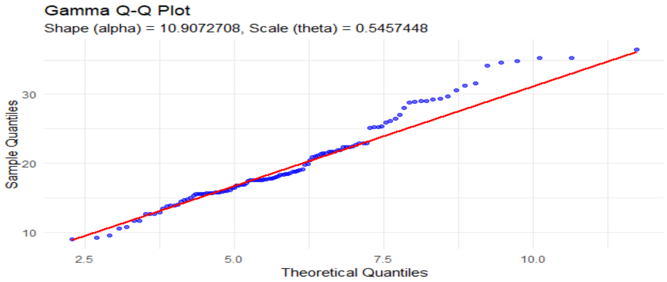

Figure 2. QQ plot of the gamma distribution

Based on Figures 1 and 2, the Gamma distribution is a suitable model for representing the motor vehicle insurance claim payment data. This visual assessment indicates that the theoretical distribution aligns well with the overall pattern of the empirical data. The similarity between the curve shape and the observed data distribution suggests a good initial model fit. Thus, from a graphical perspective, the Gamma distribution appears appropriate for this dataset.

However, conclusions based solely on visual interpretation may be subjective and potentially biased. Graphical analysis does not provide a definitive statistical measure of model accuracy. Therefore, a more objective and rigorous evaluation is required to strengthen the validity of the conclusion. This ensures that the model's suitability is supported not only visually but also statistically.

To achieve a more statistically robust conclusion, the goodness of fit of the Gamma distribution to the empirical data must be formally tested. This evaluation is conducted using a formal statistical procedure, namely the Kolmogorov–Smirnov test. The test provides a quantitative measure of the compatibility between the empirical data and the theoretical Gamma distribution. Through this approach, the suitability of the Gamma distribution model can be assessed more objectively and scientifically.

Let X be a random variable representing the paid amount value, and let F(x) denote the cumulative distribution function of the Gamma distribution with parameter estimates based on Table 2. This function represents the theoretical probability distribution that models the behavior of the paid amount data. The Gamma distribution is used to model the data's probability distribution based on the estimated parameters. Thus, F(x) serves as the reference distribution for subsequent analysis.

Given the observed paid amount data, let $F_n(x)$ represent the empirical distribution function of the data. The empirical distribution function reflects the actual distribution pattern derived directly from the observed sample. It provides a nonparametric representation of the data without assuming any specific underlying distribution. Therefore, $F_n(x)$ is used as the benchmark for comparing the theoretical model with real observations.

The goodness-of-fit test is conducted using the Kolmogorov–Smirnov test to evaluate the compatibility between F(x) and $F_n(x)$. This test measures the maximum distance between the theoretical and empirical distribution functions. The resulting statistic provides an objective criterion for assessing how well the Gamma distribution fits the observed data. Through this test, the adequacy of the Gamma distribution model can be evaluated in a statistically rigorous manner. The goodness-of-fit test using the Kolmogorov–Smirnov test is presented as follows:

1. Hypotheses
   H_0: The data are appropriately modeled by the Gamma distribution (α = 10,9072708, θ = 0,5457448)
   H_1: The data are not appropriately modeled by the Gamma distribution (α=10,9072708, θ = 0, 5457448)
2. Significance Level
   A significance level α = 0,05
3. Test Statistic
   The Kolmogorov–Smirnov test statistic is defined as follows:
   $\mathrm{T} = M\frac{MAX}{T \leq x \leq u} \mid \mathrm{F_n(x) - F(x)} \mid$
   Based on the Kolmogorov–Smirnov test results for the paid amount data, the test statistic value obtained is T = 0,9292
4. Decision Rule
   At a significance level of $\alpha = 0.05$, the decision rule is to reject $\mathrm{H_0}$ if T > critical value = $\frac{1,36}{\sqrt{113}} \approx 0{,}0120$
5. Conclusion
   Based on the test results, the Kolmogorov–Smirnov test statistic value of $T = 0{,}9292$ is greater than the critical value of 0.0120 at the significance level $\alpha = 0.05$. Therefore, the null hypothesis is rejected. It can be concluded that the paid amount data are appropriately modeled by the Gamma distribution with parameters $\alpha = 10{,}9072708$ and $\theta = 0{,}5457448$.

The parameter estimation results indicate that the Gamma distribution effectively represents the characteristics of the claim data. This suggests that the distribution is appropriate for capturing the underlying pattern of paid amounts. The estimation process provides quantitative support for the Gamma model's suitability. Therefore, the Gamma distribution is considered reliable for modeling the claim data in this study.

Based on the estimation process, the shape parameter is obtained as α = 10.9072708 and the rate parameter as θ = 0,5457448. These parameter values describe the form and spread of the Gamma distribution. The shape parameter reflects the distribution's structure, while the rate parameter controls the scale of the data. Together, they define the behavior of the modeled distribution.

The scale parameter is derived from the relationship θ = 1/λ, yielding θ = 1,832995. This transformation allows the distribution to be expressed in the scale-parameter form. Accordingly, the Gamma distribution used to model the paid amount data can be expressed as X~Gamma (10,9072708; 0,5457448). This formulation represents the final probabilistic model used in the analysis.

After obtaining the most appropriate distribution model, the next step is to measure extreme loss risk using VaR. VaR is defined as the maximum potential loss that may occur at a given confidence level over a specified observation period. This concept provides a quantitative measure of risk by identifying a critical loss threshold under normal market conditions. Therefore, VaR serves as an important tool for assessing potential financial risk exposure.

In other words, VaR represents a loss threshold that, with probability p, will not be exceeded. This means that the probability of losses surpassing the VaR value is only 1-p. The measure focuses on the tail of the loss distribution, where extreme events occur. As a result, VaR is widely used to evaluate the risk of rare but significant losses.

Mathematically, VaR can be expressed as a quantile of the loss distribution. It is defined as the inverse of the cumulative distribution function at confidence level p. This formulation allows VaR to be directly derived from the chosen probabilistic model. Thus, VaR provides a formal and model-based approach to quantifying extreme loss risk. VaR can be expressed as follows:

Table 3. Table Value at Risk Data Paid Amount

Var (95%)	30,8716
Var (99%)	36,687

Based on Table 3. The results indicate that the VaR at the 95% confidence level is 30.8716, while at the 99% confidence level it is 36.687. These values represent the maximum potential losses that are unlikely to be exceeded within their respective confidence levels. The difference between these two values illustrates the sensitivity of risk estimates to changes in confidence levels. This provides a clearer picture of how risk exposure varies under different probability thresholds.

These findings show that the VaR value increases as the confidence level increases. This pattern reflects the growing level of uncertainty and risk associated with more extreme events. Higher confidence levels correspond to rarer but more severe potential losses. Therefore, the increase in VaR is consistent with the theoretical properties of risk quantile measures.

The results also reflect a higher potential loss that must be anticipated in the event of extreme claim occurrences. This highlights the importance of incorporating high-confidence risk measures in financial and insurance risk management. By considering VaR at different confidence levels, institutions can better prepare for both moderate and extreme loss scenarios. Consequently, these findings support the use of VaR as a reliable tool for extreme risk assessment.

From an interpretative perspective, a VaR value of 30.8716 at the 95% confidence level implies that, with 95% confidence, the claim amount is not expected to exceed this value. In other words, there is only a 5% probability that the claim will surpass this threshold. This indicates that losses above this level are relatively rare under normal conditions. Therefore, this VaR value represents a reasonable upper bound for expected losses in most situations.

This interpretation reflects the role of VaR as a probabilistic risk limit. The 95% confidence level focuses on moderate extreme events that may still occur with a small probability. It helps decision-makers understand the level of risk that can be tolerated in routine risk management. As a result, this threshold serves as a practical benchmark for managing financial exposure.

Meanwhile, a VaR value of 36.687 at the 99% confidence level indicates that, with 99% confidence, the claim amount is not expected to exceed 36.687. This implies that there is only a 1% probability that the claim will exceed this value. Such a high confidence level represents more extreme and rare loss events. Consequently, this VaR value reflects a more conservative risk estimate, useful for anticipating severe but unlikely claim scenarios.

4. CONCLUSION

Based on the research findings, the Gamma distribution effectively models the number of motor vehicle insurance claims, as indicated by the data's positive and right-skewed characteristics and supported by parameter estimation and goodness-of-fit tests. However, this study has not conducted additional validation through Monte Carlo simulation, so further evaluation is still needed to comprehensively test the model's stability. Using the Gamma distribution model, Value at Risk (VaR) is estimated at 30.8716 at a 95% confidence level and 36.687 at a 99% confidence level, which can serve as a threshold for the maximum potential claims that may occur during the observation period. These findings suggest that the Gamma distribution-based VaR approach has the potential to be an effective tool for insurance companies in risk management, particularly in determining more accurate claim limits and supporting decision-making, although these results still need to be validated through Monte Carlo simulations in future research.

However, this study has several limitations, including the use of claim data from a single insurance company and a specific time period, as well as the exclusion of other risk factors, such as vehicle type or claim causes. Therefore, future research is recommended to employ larger datasets, consider alternative distributions or extreme-value approaches, and combine VaR with other risk measures to obtain a more comprehensive risk estimate. Accordingly, this study is expected to serve as an initial reference for applying quantitative methods to optimize motor vehicle insurance claim risk management.

REFERENCES

[1] A. F. Alfani, M. A. Mujib, and F. A. Ikhsan, “Tingkat kemacetan dan realita transportasi di Jalan Letjen Suprapto”, *SOSEARCH Soc. Sci. Educ. Res.*, vol. 1(1), no. 1, pp. 1–12, 2020.

[2] S. Inayah, I. A. W. Yusuf, and A. Farihin, “Faktor penyebab kemacetan lalu lintas di Kecamatan Gedebage Kota Bandung”, *Sosiosaintika*, vol. 3, no. 1, pp. 11–20, 2025, doi: 10.59996/sosiosaintika.v3i1.746.

[3] D. Dewanto *et al.*, “Peningkatan literasi polis standar kendaraan bermotor indonesia pada warga DKI Jakarta”, *J. Abdimas Dedik. Kesatuan*, vol. 6, no. 2, pp. 149–154, 2025, doi: 10.37641/jadkes.v6i2.4499.

[4] S. Zulkifli, L. Meidina, S. H. Dhalimunthe, and I. C. Ginting, “Implementasi prinsip subrogasi pada asuransi kendaraan bermotor: Studi pada PT Pan Pacific Insurance”, *SIGn J. Huk.*, vol. 2, no. 1, pp. 20–29, 2020, doi: 10.37276/sjh.v2i1.65.

[5] S. Nurmalasari and D. P. Anggraini, “Pengukuran risiko perusahaan asuransi menggunakan VaR dan TvaR”, *UMBARA J. Math. Actuar. Sci. Stat.*, vol. 1, no. 1, pp. 27–33, 2025.

[6] D. R. Simamora, I. F. Sagala, and Y. K. Yamin, “Menentukan tarif premi asuransi kendaraan bermotor berdasarkan data klaim dengan distribusi Poisson dan Gamma”, *VISA J. Visions Ideas Vol*, vol. 4, no. 1, pp. 59–67, 2024.

[7] N. Bima Sakti, S. Rosita, and S. Resti, “Perhitungan premi risiko pada data klaim asuransi kendaraan bermotor di PT Asuransi Wahana Tata cabang Bukittinggi”, *Prem. Insur. Bus. J.*, vol. 11, no. 2, pp. 19–29, 2024.

[8] A. Solihatun, L. Gubu, A. Aswani, E. Cahyono, and L. O. Saidi, “Perhitungan value at risk (VaR) pada portofolio saham IDX sektor keuangan (IDXFinance) menggunakan

metode simulasi historis (historical simulation method)", *J. Mat. Komputasi dan Stat.*, vol. 3, no. April, pp. 245–254, 2023.

[9] W. K. Rahman, "Analisis value at risk (VaR) pada saham sektor perbankan indonesia dengan metode simulasi Monte Carlo", *JATI ((Jurnal Mhs. Tek. Inform.*, vol. 8, no. 4, pp. 5895–5899, 2024.

[10] U. Mukhaiyar, A. Dianpermatasari, and A. Dzakiya, "The value at risk analysis using heavy-tailed distribution on the insurance claims data", *JTAM (Jurnal Teor. dan Apl. Mat.*, vol. 8, no. 4, pp. 1233–1248, 2024.

[11] I. Susanto and S. S. Handajani, "Pengelompokan rumah tangga di indonesia berdasarkan pendapatan per kapita dengan model finite mixture", *MEDIA Stat.*, vol. 13, no. 1, pp. 13–24, 2020, doi: 10.14710/medstat.13.1.13-24.

[12] I. Hasanah, W. Irawan, and I. A. Yakin, "Truncated Gamma-Truncated Lomax distribution in modelling data claims", *Int. J. Comput. Sci. Appl. Math.*, vol. 10, no. 2, pp. 2023–2025, 2024.

[13] R. Dapa and I. T. Utami, "Penentuan rate asuransi kendaraan bermotor menggunakan kredibilitas Bayesian", *Indones. J. Appl. Stat.*, vol. 6, no. 1, p. 33, 2024, doi: 10.13057/ijas.v6i1.79813.

[14] N. A. S. W. R. Hendra Perdana, "Analisis risiko portofolio lq45 menggunakan pendekatan value at risk block maxima-generalized extreme value", *Bimaster Bul. Ilm. Mat. Stat. dan Ter.*, vol. 9, no. 2, pp. 267–274, 2020, doi: 10.26418/bbimst.v9i2.39914.

[15] K. Syuhada *et al.*, "Enhancing value-at-risk with credible expected risk models", *Int. J. Financ. Stud.*, vol. 12, no. 3, 2024, doi: 10.3390/ijfs12030080.

[16] I. Applications *et al.*, "Simulasi jumlah klaim agregasi berdistribusi Poisson dengan besar klaim berdistribusi Gamma dan Rayleigh", vol. 17, no. 2, pp. 173–180, 2020.

[17] T. Yulita, M. Patricia, A. Sofian, and E. Hidayat, "Penentuan premi murni dari data klaim asuransi kendaraan roda empat dengan jenis perlindungan comprehensive", *Var. J. Stat. Its Appl.*, vol. 6, no. April, pp. 75–86, 2024.