Malaysian Journal of Mathematical Sciences 19(1): 79–98 (2025)
https://doi.org/10.47836/mjms.19.1.05

Malaysian Journal of Mathematical Sciences

Journal homepage: https://mjms.upm.edu.my

A Comparison of The Fuzzy Models of The Impact of Corticosterone in Statistical Analysis

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Received: 29 May 2024
Accepted: 20 September 2024

Abstract

Nowadays, fuzzy concepts are frequently used as statistical parameters, while the traditional normal distribution can only accept determinate variable. Article is studied about new notion of general distribution, in order to design a practical application of fuzzy model are using generalized Rayleigh distribution, Rayleigh distribution and Log-Logistic distribution for clarifying the effect of corticosterone, we discussed multiple states fuzzy mathematical models in the present study. Furthermore, a comparative study is developed utilizing hypothesis testing between the expected levels of respiratory modifications following corticosterone the injection for various distribution models.

Keywords: fuzzy model; hypothesis testing; Rayleigh distribution; Log-Logistic distribution.

1 Introduction

The normal distribution plays a crucial role in mathematical statistics and probability theory, both in theory and in practice. It is commonly seen in many domains, including high technology, manufacturing, and natural occurrences. Typically, an index with a normal distribution is influenced by a large number of tiny random factors. For instance, a group characteristic like class size, plant length, or rice stem diameter in a particular area; quality indicators for all product types like tool size, capacitor capacitance, fiber tension, or plant length; or measured data events like highest air temperature, average rainfall, or humidity.

One of the most significant and often used probability distributions in statistics is the normal distribution, sometimes referred to as the Gaussian distribution. Its key characteristics include mean, median, mode, symmetry, variance, and standard deviation. The normal distribution is characterized by a bell-shaped curve that is symmetric around the mean. If you want to describe continuous variables like heights, test scores, measurement mistakes, and more that cluster around a central value, you can use the normal distribution. We can do hypothesis testing, draw conclusions, and compute probabilities with it. Statistical distributions are mathematical functions that describe the likelihood or frequency of different outcomes in a dataset or random process. Common statistical distributions include the Poisson, Binomial, Chi-Square, Normal (Gaussian), and Exponential distributions. Understanding the properties of these distributions is crucial for statistical analysis, hypothesis testing, and data modeling. The parameters of these distributions, such as their mean, variance, and shape, allow them to model a wide range of real-world phenomena in fields like biology, economics, and more.

The underlying statistical model or distributions have a significant impact on the importance of the techniques utilized in a statistical investigation. Determining generalizations about a population from data from a sample of that group is the goal of statistical interpretation. The process of hypothesis testing evaluates the strength of the evidence obtained from the sample and offers support for conclusions pertaining to the population. Stated differently, it provides a means of determining the degree to which empirical findings from a study sample can be extrapolated to the larger population from which the sample was selected. A technique of parametric testing statistical predictions for fuzzy random variables was presented by Hesamian and Sham [8]. Fuzzy hypothesis testing was created by Yosefi et al. [17] by utilizing the likelihood ratio statistic. An animal must experience stress in order for its biological response mechanisms to work to restore homeostasis [3]. The biological reaction to stress is undoubtedly inconsistent, and its effects might vary greatly [4]. However, the fundamental definition of stress has always been based on how physiology and behaviour change in response to unpleasant stimuli [14, 10]. Birds must deal with extreme stressors like bad weather, a lack of food, predation, competition, and disruption in order to thrive in any environment. It is widely acknowledged that fewer birds are being impacted by the stress hormone corticosterone [13, 9].

Therefore, antiretroviral medication, surveillance, and diagnosis of hens are crucial [6, 11]. Fuzzy Distribution Set (FDS) is a new kind of fuzzy set introduced by Batyrshin [1]. It is defined as fuzzy sets on a finite domain where the sum of the membership values must equal 1. Subjective probability distributions and subjective weight distributions can be modeled by such fuzzy sets. New parametric negations of probability distributions based on the involutive negation of PD were presented by Batyrshin et al. [2]. It was recently suggested that probability distributions be thought of as fuzzy distribution sets, opening the door for many fuzzy set concepts and operations to be extended to probability distributions. A probabilistic approach is presented by Fakoor and Alizadeh Kaklar [7] for determining the Weibull distribution parameters, which lessen the impact of the percentage discretization error on the experimental fatigue life and R-S-N curves for three reliability levels. Artificial data are produced and the accuracy of the common Weibull distribution model can be increased by treating every normal fatigue test result as an analogous Weibull distribution. Castilloa and Fernández-Canteli [5] are discussed about the Weibull model and compatible regression of Weibull model for the description of the three-dimensional fatigue σ_M–N–R field as a basis for elative damage approach.

In order to bridge this gap, Li et al. [12] and colleagues proposed an estimation method of the process performance index for the two-parameter exponential distribution with measurement errors. They also derived the relationship between the unobservable actual value and measurement value, which is regarded as the full error model, and studied the maximum likelihood estimation method to obtain the unknown parameters. Shama et al. [15] introduced and examined a modified Weibull distribution that includes four parameters and may adequately depict a bathtub-shaped hazard rate function. Because of its capacity to represent both rising and falling failure rates, it is important in the domains of longevity and dependability. Shrahili et al. [16] tackle the problem of estimating different entropy measures for an LL distribution using progressive type II filtering. We provide equations for six distinct categories of entropy assessments. The greatest likelihood approach is used to produce the estimators of the proposed entropy metrics. For the entropy metrics talked about, approximate confidence intervals are generated.

In the current study, we will cover the fuzzy mathematical models for the Generalized Rayleigh distribution (GRD), Rayleigh distribution (RD), and Log-Logistic distribution. The GRD, RD, and Log-Logistic distribution are used to explain the effect of corticosterone. Furthermore, a comparison between the predicted levels of respiratory changes following corticosterone treatment for various distribution models has been developed using hypothesis testing. The preliminaries used in this article were presented in Section 2 of the document, which was organized as follows. GRD , RD, and Log-Logistic distributions (LLD) were used to introduce the various types of fuzzy mathematical models in Section 3. By determining the mean as well as the variance values, we were able to determine the effect of corticosterone in Section 4 by applying the models previously discussed. In Section 5, we compare the mean and variance values of the different scenarios utilizing testing of hypotheses. A brief conclusion is provided in Section 6.

Notation:

λ	:	Scale parameter of GGD
μ, ψ	:	Shape parameter of GGD
δ	:	Scale parameter of LLD
ψ	:	Shape parameter of GGD
β	:	Scale parameter of RD and GRD
χ	:	Shape parameter of RD and GRD
$\overline{\lambda}[x_\gamma^U]$	:	Alpha cut of scale value in GGD
$\overline{\phi}[x_\gamma^U], \overline{\mu}[x_\gamma^U]$	:	Alpha cut of shape value in GGD
$\overline{\eta}[x_\gamma^U]$	:	Alpha cut of scale value in LLD
$\overline{\psi}[x_\gamma^U]$	:	Alpha cut of shape value in LLD
$\overline{\beta}[x_\gamma^U]$	:	Alpha cut of scale value in RD and GRD

$\overline{\chi}[x_\gamma^U]$	:	Alpha cut of shape value in RD and GRD
$\mathrm{E}[x_\gamma^U]$	:	Mean value of X
$V[x_\gamma^U]$	:	Variance value of X
$\overline{E}[x_\gamma^U]$	:	Fuzzy mean value of X
$\overline{V}[x_\gamma^U]$	:	Fuzzy variance value of X

2 Preliminaries

Definition 2.1. *A measurable function $\mathrm{X}_\gamma^U : \Omega_\gamma^U \to E_\gamma^U$ that maps a collection of potential outcomes from a sample space Ω_γ^U to a measurable space E_γ^U is what defines a random variable X_γ^U . The sample space Ω_γ^U must be a sample space of a probability triple $\left(\Omega_\lambda^U, F_\gamma^U, P_\gamma^U\right)$ in order to meet the technical axiomatic definition.*

Definition 2.2. *The gamma function, denoted as (the Greek capital letter gamma), is an accepted extension of the factorial function to complex numbers. For any complex values other than non-positive integers, a gamma function is defined. For any positive integer n, $\Gamma(\delta) = (\delta - 1)!$.*

The gamma function is defined by a convergent improper integral,

$$\Gamma(\delta) = \int_0^\infty \gamma^{\delta-1} e^{-\gamma} d\gamma, \qquad \Re(\delta) > 0.$$

2.1 Property:

Any real-valued random variable's cumulative distribution function has one of the following properties:

1. $F_\gamma^U(\gamma)$ is non-decreasing.
2. $F_\gamma^U(\gamma)$ is right-continuous.
3. $0 \leq F_\gamma^U(\gamma) \leq 1$.
4. $F_\gamma^U\ (X) = 0$ and $F_\gamma^U\ (Y) = 1$.
5. $P_\gamma^U\left(a_\gamma^U < X_\gamma^U \leq b_\gamma^U\right) = F_\gamma^U\left(b_\gamma^U\right) - F_\gamma^U\left(a_\gamma^U\right)$.

2.2 Absolutely continuous random variable

A Real Random variable X_γ^U has an absolutely continuous probability distribution if there is a function $f_\gamma^U : \Re \to [0, \infty]$ such that for each interval $[a, b] \subset \Re$ the probability of X_γ^U belongs to $[a, b]$ is given by the integral of f f_γ^U over I_γ^U then $P_\gamma^U\left(a_\gamma^U < X_\gamma^U \leq b_\gamma^U\right) = \int_{a_\gamma^U}^{b_\gamma^U} f_\gamma^U(\gamma)\, d\gamma$.

This is how a probability density function is described, indicating that probability distributions that are absolutely continuous are exactly those that have a probability density function. Particularly, the likelihood of X_γ^U to take any single value a_γ^U is zero, because an integral with coinciding upper and lower limits is always equal to zero. If the interval $\left(a_\gamma^U, b_\gamma^U\right)$ is replaced by any measurable set A_γ^U, the according equality still holds $P_\gamma^U\left(X_\gamma^U \in A_\gamma^U\right) = \int_{A_\gamma^U} f_\gamma^U(\gamma)\,d\gamma$. An absolutely continuous random variable is a random variable whose probability distribution is absolutely continuous.

Theorem 2.1. *Prove that* $\Gamma(\delta+1) = \delta!$.

Proof.

$$\Gamma(\delta+1) = \int_0^\infty \gamma^\delta e^{-\gamma} d\gamma,$$
$$\Gamma(\delta+1) = \left[-\gamma^\delta e^{-\gamma}\right]_0^\infty + \int_0^\infty \delta\gamma^{\delta-1} e^{-\gamma} d\gamma,$$
$$\Gamma(\delta+1) = \lim t \to \infty\left(-\gamma^\delta e^{-\gamma}\right) + \left(-0^\delta e^{-0}\right) + \int_0^\infty \delta\gamma^{\delta-1} e^{-\gamma} d\gamma,$$
$$\Gamma(\delta+1) = \delta\int_0^\infty \delta^{\gamma-1} e^{-\gamma} d\gamma,$$
$$\Gamma(\delta+1) = \delta\Gamma(\delta),$$
$$\Gamma(\delta+1) = \delta(\delta-1)!,$$
$$\Gamma(\delta+1) = \delta!.$$

□

2.3 Generalized Rayleigh distribution

A random variable X_γ^U follows the GRD has probability density function of the form,

$$f(\gamma:\chi,\beta) = \frac{2}{\Gamma(\chi+1)\,\beta^{\chi+1}}\chi^{2\beta+1} e^{\frac{\gamma^2}{\chi}}, \qquad \gamma > 0,$$

where $\chi \geq 0$ is the shape parameter and $\beta \geq 0$ is the scale parameter. The expected value and variance of GRD,

$$E(X_\gamma^U) = \frac{\Gamma\left(\chi+\frac{3}{2}\right)}{\Gamma(\chi+1)}\sqrt{\beta}, \quad \text{and} \quad V(X_\gamma^U) = \left[(\chi+1) - \left(\frac{\Gamma\left(\chi+\frac{3}{2}\right)}{\Gamma(\chi+1)}\right)^2\right]\beta.$$

2.4 Rayleigh distribution

Consider the two-dimensional vector $\Upsilon_\gamma^U = \left(U_\gamma^U, V_\gamma^U\right)$ which has components that are bivariate normally distributed, centered at zero, and independent. Then U_γ^U and V_γ^U have density functions,

$$f_{U_\gamma^U}(\gamma:\beta) = f_{V_\gamma^U}(\gamma:\beta) = \frac{e^{-\frac{\gamma^2}{2\beta^2}}}{\sqrt{2\pi\beta^2}}.$$

Let, X_γ^U be the length of Y_γ^U. That is, $X_\gamma^U = \sqrt{\left(U_\gamma^U\right)^2 + \left(V_\gamma^U\right)^2}$.

Then, X_γ^U has cumulative distribution function,

$$F_{X_\gamma^U}(\gamma:\beta)=\iint_{D_\gamma} f_{U_\gamma^U}\left(u_\gamma^U:\beta\right) f_{V_\gamma^U}\left(v_\gamma^U:\beta\right) d\mathrm{A},$$

where D_γ is the disk,

$$D_\gamma=\left\{\left(U_\gamma^U, V_\gamma^U\right):\sqrt{\left(U_\gamma^U\right)^2+\left(V_\gamma^U\right)^2}\leq\gamma\right\}.$$

It becomes,

$$F_{X_\gamma^U}(\gamma:\beta)=\frac{1}{2\pi\beta^2}\int_0^{2\pi}\int_0^{\gamma}\gamma e^{-\frac{\gamma^2}{\beta^2}}d\gamma d\theta,$$
$$F_{X_\gamma^U}(\gamma:\beta)=\frac{1}{\beta^2}\int_0^{\gamma}\gamma e^{-\frac{\gamma^2}{2\beta^2}}d\gamma.$$

Finally, the probability function for is the derivative of its cumulative distribution function is

$$f(\gamma:\beta)=\frac{d}{d\gamma}F_{X_\gamma^U}(\gamma:\beta)=\frac{\gamma}{\beta^2}e^{\frac{1}{2}\left(\frac{\gamma}{\beta}\right)^2},\quad \text{where}\quad 0\leq\gamma\leq\infty,\qquad \beta>0.$$

This is the Rayleigh distribution.

The cumulative Rayleigh distribution function is $F(\gamma:\beta)=1-e^{\frac{-\gamma^2}{2\beta^2}},\quad \gamma\in[0,\infty)$.

The mean and variance of Rayleigh distribution $E(X_\gamma^U)=\beta\sqrt{\frac{\pi}{2}}$ and $V(X_\gamma^U)=\beta^2\left(2-\frac{\pi}{2}\right)$.

2.5 Log–Logistic distribution

The parameter $\eta>0$ is a scale parameter and is also median of the distribution. The parameter $\psi>0$ is a shape parameter. The distribution is unimodal when $\psi>1$ and its dispersion decreases as ψ increases.

The cumulative distribution function is

$$F(\gamma:\eta,\psi)=\frac{1}{1+\left(\frac{\gamma}{\eta}\right)^{-\psi}},$$

$$F(\gamma:\eta,\psi)=\frac{\left(\frac{\gamma}{\eta}\right)^{\psi}}{1+\left(\frac{\gamma}{\eta}\right)^{\psi}},$$

$$F(\gamma:\eta,\psi)=\frac{(\gamma)^{\psi}}{(\eta)^{\psi}+(\gamma)^{\psi}},$$

where $\gamma>0$, $\eta>0$, $\psi>0$.

The probability density function of Log-Logistic distribution is

$$f(\gamma:\eta,\psi)=\frac{\left(\frac{\psi}{\eta}\right)\left(\frac{\gamma}{\eta}\right)^{\psi-1}}{\left(1+\left(\frac{\gamma}{\eta}\right)^{\psi}\right)^{2}},\qquad \gamma>0,\qquad \eta>0,\qquad \psi\geq 1.$$

The expected value and variance value of Log-Logistic distribution,

$$E(X_{\gamma}^{U})=\frac{\eta\left(\frac{\pi}{\psi}\right)}{\sin\left(\frac{\pi}{\psi}\right)},$$

$$V(X_{\gamma}^{U})=\frac{\eta^{2}\left[\left(\frac{2\pi}{\psi}\right)\sin 2\left(\frac{\pi}{\psi}\right)-\left(\frac{\pi}{\psi}\right)^{2}\right]}{\sin^{2}\left(\frac{\pi}{\psi}\right)}.$$

2.6 Generalized gamma distribution

The probability density function of generalized gamma distribution is

$$f(\gamma:\lambda,\mu,\phi)=\frac{\lambda\gamma^{\lambda\phi-1}e^{-\left(\frac{\gamma}{\mu}\right)^{\lambda}}}{\mu^{\lambda\phi}\Gamma(\phi)}\ ,\qquad \gamma>0.$$

The expected value and variance value of generalized gamma distribution,

$$E[X_{\gamma}^{U}]=\frac{\mu\Gamma\left(\frac{\phi+1}{\lambda}\right)}{\Gamma\phi},$$

$$V[X_{\gamma}^{U}]=\mu^{2}\left(\frac{\Gamma\left(\frac{\phi+2}{\lambda}\right)}{\Gamma\phi}-\left(\frac{\Gamma\left(\frac{\phi+1}{\lambda}\right)}{\Gamma\phi}\right)^{2}\right).$$

3 New Finding

3.1 Fuzzy expected value and fuzzy variance value of fuzzy Log-Logistic distribution model

A random variable χ_{δ}^{U} as follows Fuzzy Log-logistic distribution (FLLD) with the fuzzy numbers $\overline{\delta},\overline{\psi}$ is indicated by $\chi_{\delta}^{U}\sim FLLD(\gamma,\overline{\delta},\overline{\psi})$.

The expected value for $\chi_{\delta}^{U}\sim FLLD\left(\gamma,\overline{\delta},\overline{\psi}\right)$ is

$$\overline{\mathcal{E}}(\chi_{\delta}^{U})=\left\{\mathcal{E}\left(\chi_{\delta}^{U}\right)[\alpha],\mu_{\mathcal{E}\left(\chi_{\delta}^{U}\right)}/\mathcal{E}\left(\chi_{\delta}^{U}\right)[\alpha]=\mathcal{E}_{L}\left(\chi_{\delta}^{U}\right)[\alpha],\mathcal{E}_{U}\left(\chi_{\delta}^{U}\right)[\alpha],\mu_{\mathcal{E}\left(\chi_{\delta}^{U}\right)}\left(\chi_{\delta}^{U}\right)=\alpha\right\},$$

$$\overline{\mathcal{E}}_{L}\left(\chi_{\delta}^{U}\right)[\alpha]=\inf\left\{\mathcal{E}\left(\chi_{\delta}^{U}\right)[\alpha]/\overline{\delta}\in\overline{\delta}(\alpha),\quad \overline{\psi}\in\overline{\psi}(\alpha)\right\},$$

$$\overline{\mathcal{E}}_{U}\left(\chi_{\delta}^{U}\right)[\alpha]=\sup\left\{\mathcal{E}\left(\chi_{\delta}^{U}\right)[\alpha]/\overline{\delta}\in\overline{\delta}(\alpha),\quad \overline{\psi}\in\overline{\psi}(\alpha)\right\},$$

$$\overline{\mathcal{E}}_{L}\left(\chi_{\delta}^{U}\right)=\left(\frac{\overline{\delta}(\frac{\pi}{\overline{\psi}})}{\sin\left(\frac{\pi}{\overline{\psi}}\right)}\right),\qquad \overline{\delta}\in\overline{\delta}(\alpha),\qquad \overline{\psi}\in\overline{\psi}(\alpha).$$

The variance value for $\boldsymbol{\chi_\delta^U \sim FLLD(\gamma, \overline{\delta}, \overline{\psi})}$ is

$$\begin{aligned}
\overline{\mathcal{V}}(\chi_\delta^U) &= \left\{ \mathcal{V}\left(\chi_\delta^U\right)[\alpha], \mu_{\mathcal{V}\left(\chi_\delta^U\right)} / \mathcal{V}\left(\chi_\delta^U\right)[\alpha] = \mathcal{V}_L\left(\chi_\delta^U\right)[\alpha], \mathcal{V}_U\left(\chi_\delta^U\right)[\alpha], \mu_{\mathcal{V}\left(\chi_\delta^U\right)}\left(\chi_\delta^U\right) = \alpha \right\}, \\
\left(\chi_\delta^U\right)[\alpha] &= \inf\left\{ \mathcal{V}\left(\chi_\delta^U\right)[\alpha] / \overline{\delta} \in \overline{\delta}(\alpha), \quad \overline{\psi} \in \overline{\psi}(\alpha) \right\}, \\
\overline{\mathcal{V}}_U\left(\chi_\delta^U\right)[\alpha] &= \sup\left\{ \mathcal{V}\left(\chi_\delta^U\right)[\alpha] / \overline{\delta} \in \overline{\delta}(\alpha), \quad \overline{\psi} \in \overline{\psi}(\alpha) \right\}, \\
\overline{\mathcal{V}}(\chi_\delta^U) &= \left(\frac{\overline{\delta}^2 \left[\left(\frac{2\pi}{\overline{\psi}}\right) sin\, 2\left(\frac{\pi}{\overline{\psi}}\right) - \left(\frac{\pi}{\overline{\psi}}\right)^2 \right]}{sin^2\left(\frac{\pi}{\overline{\psi}}\right)} \right), \qquad \overline{\delta} \in \overline{\delta}(\alpha), \qquad \overline{\psi} \in \overline{\psi}(\alpha).
\end{aligned}$$

3.2 Fuzzy expected value and fuzzy variance value of fuzzy Rayleigh distribution model

A random variable χ_δ^U follows fuzzy Rayleigh distribution is denoted by $\chi_\delta^U \sim FRD(\gamma, \overline{\beta})$.

The mean of fuzzy Rayleigh distribution is given by,

$$\begin{aligned}
\overline{\mathcal{E}}(\chi_\delta^U) &= \left\{ \mathcal{E}\left(\chi_\delta^U\right)[\alpha], \mu_{\mathcal{E}\left(\chi_\delta^U\right)} / \mathcal{E}\left(\chi_\delta^U\right)[\alpha] = \mathcal{E}_L\left(\chi_\delta^U\right)[\alpha], \mathcal{E}_U\left(\chi_\delta^U\right)[\alpha], \mu_{\mathcal{E}\left(\chi_\delta^U\right)}\left(\chi_\delta^U\right) = \alpha \right\}, \\
\overline{\mathcal{E}}_L\left(\chi_\delta^U\right)[\alpha] &= \inf\left\{ \mathcal{E}\left(\chi_\delta^U\right) / \overline{\beta} \in \overline{\beta}(\alpha) \right\}, \\
\overline{\mathcal{E}}_U\left(\chi_\delta^U\right)[\alpha] &= \sup\left\{ \mathcal{E}\left(\chi_\delta^U\right) / \overline{\beta} \in \overline{\beta}(\alpha) \right\}, \\
\mathcal{E}\left(\chi_\delta^U\right) &= \overline{\beta}\sqrt{\frac{\pi}{2}}.
\end{aligned}$$

The variance of fuzzy Rayleigh distribution is given by,

$$\begin{aligned}
\overline{\mathcal{V}}(\chi_\delta^U) &= \left\{ \mathcal{V}\left(\chi_\delta^U\right)[\alpha], \mu_{\mathcal{V}\left(\chi_\delta^U\right)} / \mathcal{V}\left(\chi_\delta^U\right)[\alpha] = \mathcal{V}_L\left(\chi_\delta^U\right)[\alpha], \mathcal{V}_U\left(\chi_\delta^U\right)[\alpha], \mu_{\mathcal{V}\left(\chi_\delta^U\right)}\left(\chi_\delta^U\right) = \alpha \right\}, \\
\overline{\mathcal{V}}_L\left(\chi_\delta^U\right)[\alpha] &= \inf\left\{ \mathcal{E}\left(\chi_\delta^U\right) / \overline{\beta} \in \overline{\beta}(\alpha) \right\}, \\
\overline{\mathcal{V}}_U\left(\chi_\delta^U\right)[\alpha] &= \sup\left\{ \mathcal{E}\left(\chi_\delta^U\right) / \overline{\beta} \in \overline{\beta}(\alpha) \right\}, \\
\overline{\mathcal{V}}\left(\chi_\delta^U\right) &= \left(\overline{\beta}\right)^2\sqrt{\frac{\pi}{2}}.
\end{aligned}$$

3.3 Fuzzy expected value and fuzzy variance value of fuzzy generalized Rayleigh distribution

A random variable χ_δ^U follows fuzzy generalized Rayleigh distribution is denoted by, $\chi_\delta^U \sim FGRD(\gamma, \overline{\beta}, \overline{\rho})$, where $\overline{\beta}$ and $\overline{\rho}$ are fuzzy parameters.

The expected value for $\boldsymbol{\chi_\delta^U \sim FGRD(\gamma, \overline{\beta}, \overline{\rho})}$ is given by,

$$\begin{aligned}
\overline{\mathcal{E}}(\chi_\delta^U) &= \left\{ \mathcal{E}\left(\chi_\delta^U\right)[\alpha], \mu_{\mathcal{E}\left(\chi_\delta^U\right)} / \mathcal{E}\left(\chi_\delta^U\right)[\alpha] = \mathcal{E}_L\left(\chi_\delta^U\right)[\alpha], \mathcal{E}_U\left(\chi_\delta^U\right)[\alpha], \mu_{\mathcal{E}\left(\chi_\delta^U\right)}\left(\chi_\delta^U\right) = \alpha \right\}, \\
\overline{\mathcal{E}}_L\left(\chi_\delta^U\right)[\alpha] &= \inf\left\{ \mathcal{E}\left(\chi_\delta^U\right) / \overline{\rho} \in \overline{\rho}(\alpha), \quad \overline{\beta} \in \overline{\beta}(\alpha) \right\}, \\
\overline{\mathcal{E}}_U\left(\chi_\delta^U\right)[\alpha] &= \sup\left\{ \mathcal{E}\left(\chi_\delta^U\right) / \overline{\rho} \in \overline{\rho}(\alpha), \quad \overline{\beta} \in \overline{\beta}(\alpha) \right\}, \\
\mathcal{E}\left(\chi_\delta^U\right) &= \frac{\Gamma\left(\overline{\rho} + \frac{3}{2}\right)}{\Gamma\left(\overline{\rho} + 1\right)}\sqrt{\overline{\beta}}, \qquad \overline{\rho} \in \overline{\rho}(\alpha), \qquad \overline{\beta} \in \overline{\beta}(\alpha).
\end{aligned}$$

The variance value of $\chi_\delta^U \sim FGRD(\gamma, \overline{\beta}, \overline{\rho})$ is given by,

$$\overline{\mathcal{V}}(\chi_\delta^U) = \left\{ \mathcal{E}\left(\chi_\delta^U\right)[\alpha], \mu_{\mathcal{V}(\chi_\delta^U)} / \mathcal{E}\left(\chi_\delta^U\right)[\alpha] = \mathcal{E}_L\left(\chi_\delta^U\right)[\alpha], \mathcal{E}_U\left(\chi_\delta^U\right)[\alpha], \mu_{\mathcal{V}(\chi_\delta^U)}\left(\chi_\delta^U\right) = \alpha \right\},$$
$$\overline{\mathcal{V}}\left(\chi_\delta^U\right)[\alpha] = \inf\left\{\mathcal{E}\left(\chi_\delta^U\right)/\overline{\rho} \in \overline{\rho}(\alpha), \quad \overline{\beta} \in \overline{\beta}(\alpha)\right\},$$
$$\overline{\mathcal{V}}_U\left(\chi_\delta^U\right)[\alpha] = \sup\left\{\mathcal{E}\left(\chi_\delta^U\right)/\overline{\rho} \in \overline{\rho}(\alpha), \quad \overline{\beta} \in \overline{\beta}(\alpha)\right\},$$
$$\overline{\mathcal{V}}\left(\chi_\delta^U\right) = \left[(\overline{\rho}+1) - \left(\frac{\Gamma\left(\overline{\rho} + \frac{3}{2}\right)}{\Gamma\left(\overline{\rho}+1\right)} \right)^2 \right] \overline{\beta}, \quad \overline{\rho} \in \overline{\rho}(\alpha), \quad \overline{\beta} \in \overline{\beta}(\alpha).$$

Consider a random variable χ_δ^U follows fuzzy log logistic distribution with the fuzzy numbers $\overline{\delta}$, $\overline{\psi}$ as parameters is indicated by $\chi_\delta^U \sim FGRD\left(\gamma, \overline{\beta}, \overline{\rho}\right)$.

3.4 Fuzzy expected value and fuzzy variance value of generalized gamma distribution model

The probability density function of fuzzy generalized gamma distribution is

$$f\left(\gamma : \overline{\lambda}, \overline{\mu}, \overline{\varphi}\right) = \left(\frac{\overline{\lambda} \gamma^{\overline{\lambda \varphi}-1} e^{-\left(\frac{\gamma}{\overline{\mu}}\right)}}{\overline{\mu}^{\overline{\lambda \varphi}} \Gamma(\overline{\varphi})} \right).$$

A random variable follows Fuzzy Gamma distribution (FGGD) with fuzzy parameter $\overline{\lambda}$,$\overline{\mu}$, $\overline{\varphi}$ is symbolized by $\chi_\delta^U \sim FGGD\left(\overline{\lambda}, \overline{\mu}, \overline{\varphi}\right)$.

The expected value of $\chi_\delta^U \sim FGGD\left(\gamma, \overline{\lambda}, \overline{\mu}, \overline{\varphi}\right)$ is given by,

$$\overline{\mathcal{E}}(\chi_\delta^U) = \left\{ \mathcal{E}\left(\chi_\delta^U\right)[\alpha], \mu_{\mathcal{E}(\chi_\delta^U)} / \mathcal{E}\left(\chi_\delta^U\right)[\alpha] = \mathcal{E}_L\left(\chi_\delta^U\right)[\alpha], \mathcal{E}_U\left(\chi_\delta^U\right)[\alpha], \mu_{\mathcal{E}(\chi_\delta^U)}\left(\chi_\delta^U\right) = \alpha \right\},$$
$$\overline{\mathcal{E}}_L\left(\chi_\delta^U\right)[\alpha] = \inf\left\{\mathcal{E}\left(\chi_\delta^U\right)/\overline{\lambda} \in \overline{\lambda}(\alpha), \quad \overline{\mu} \in \overline{\mu}(\alpha), \quad \overline{\varphi} \in \overline{\varphi}(\alpha)\right\},$$
$$\overline{\mathcal{E}}_U\left(\chi_\delta^U\right)[\alpha] = \sup\left\{\mathcal{E}\left(\chi_\delta^U\right)/\overline{\lambda} \in \overline{\lambda}(\alpha), \quad \overline{\mu} \in \overline{\mu}(\alpha), \quad \overline{\varphi} \in \overline{\varphi}(\alpha)\right\},$$
$$\overline{\mathcal{E}}(\chi_\delta^U) = \frac{\overline{\mu}\Gamma(\overline{\varphi} + \frac{1}{\overline{\lambda}})}{\Gamma(\overline{\varphi})}, \quad \overline{\lambda} \in \overline{\lambda}(\alpha), \quad \overline{\mu} \in \overline{\mu}(\alpha), \quad \overline{\varphi} \in \overline{\varphi}(\alpha).$$

The variance value of $\chi_\delta^U \sim FGGD\left(\gamma, \overline{\lambda}, \overline{\mu}, \overline{\varphi}\right)$ is given by,

$$\overline{\mathcal{V}}(\chi_\delta^U) = \left\{ \mathcal{V}\left(\chi_\delta^U\right)[\alpha], \mu_{\mathcal{V}(\chi_\delta^U)} / \mathcal{V}\left(\chi_\delta^U\right)[\alpha] = \mathcal{V}_L\left(\chi_\delta^U\right)[\alpha], \mathcal{V}_U\left(\chi_\delta^U\right)[\alpha], \mu_{\mathcal{V}(\chi_\delta^U)}\left(\chi_\delta^U\right) = \alpha \right\},$$
$$\overline{\mathcal{V}}_L\left(\chi_\delta^U\right)[\alpha] = \inf\left\{\mathcal{V}\left(\chi_\delta^U\right)/\overline{\lambda} \in \overline{\lambda}(\alpha), \quad \overline{\mu} \in \overline{\mu}(\alpha), \quad \overline{\varphi} \in \overline{\varphi}(\alpha)\right\},$$
$$\overline{\mathcal{V}}_U\left(\chi_\delta^U\right)[\alpha] = \sup\left\{\mathcal{V}\left(\chi_\delta^U\right)/\overline{\lambda} \in \overline{\lambda}(\alpha), \quad \overline{\mu} \in \overline{\mu}(\alpha), \quad \overline{\varphi} \in \overline{\varphi}(\alpha)\right\},$$
$$\overline{\mathcal{V}}(\chi_\delta^U) = \overline{\mu}^2 \left(\frac{\Gamma\left(\overline{\varphi} + \frac{2}{\overline{\lambda}}\right)}{\Gamma\left(\overline{\varphi}\right)} - \frac{\Gamma\left(\overline{\varphi} + \frac{1}{\overline{\lambda}}\right)^2}{\Gamma\left(\overline{\varphi}\right)} \right), \quad \overline{\lambda} \in \overline{\lambda}(\alpha), \quad \overline{\mu} \in \overline{\mu}(\alpha), \quad \overline{\varphi} \in \overline{\varphi}(\alpha)$$

4 Applications

Figures 1(a–b) and 2 display the pattern of corticosterone in plasma following a handling meeting spanning one minute. The plasma corticosterone concentration reached its highest level and was significantly greater than before handling within 10 minutes of the first handling. At the 20, 30, and 40 minute sampling times, the corticosterone concentration was still significantly higher. However, by the 60 minute samples time, it had fallen back to levels that were comparable to those before handling [5]. Figures 1(a–b) and 2, the mean plasma concentration of corticosterone in response to hen being handled for one hour. As the same results shown in the Table 1 and 2.

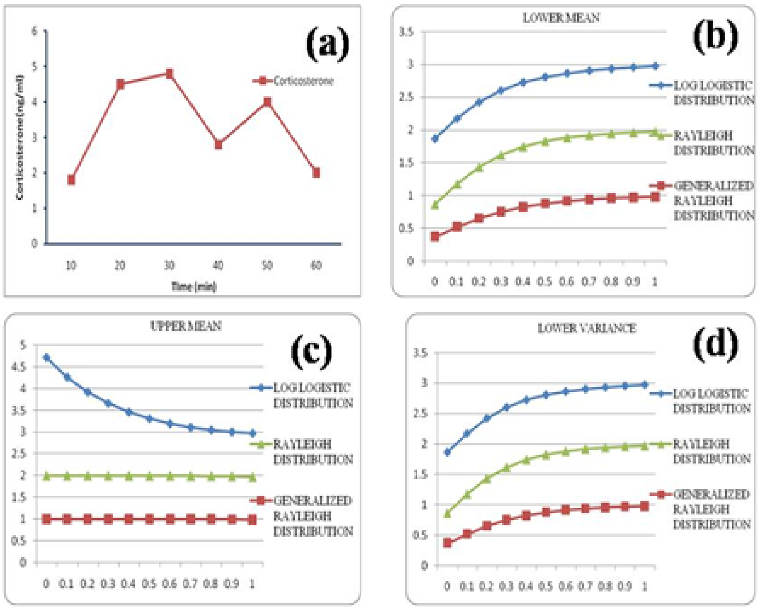

Figure 1: (a) Mean plasma concentration cortcosterone response to being handled for one hour. (b) Lower alpha cut for mean. (c) Upper alpha cut for mean. (d) Lower alpha cut for variance.

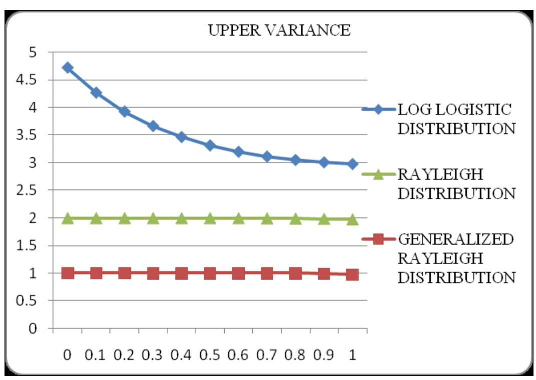

Figure 2: Upper alpha cut for variance.

Based on this study the parameters value of GRD β, χ are 1.7402 and 1.1575 respectively, the LLD parameters Value η, ψ are 2.9615 and 2.8297 respectively and the parameters value of RD β is 2.6463.

Table 1: Mean values for FGRD, FRD and FLLD.

A	$E_L[X_\gamma^U(\alpha)]$			$E_U[X_\gamma^U(\alpha)]$		
	FGRD	**FRD**	**FLLD**	**FGRD**	**FRD**	**FLLD**
0.0	1.26491	21.5576	27.1831	1.34164	26.8625	39.3732
0.1	1.27043	21.7751	27.4731	1.33940	26.5427	38.2379
0.2	1.27593	21.9997	27.7595	1.33716	26.2328	37.1500
0.3	1.28144	22.2220	28.0600	1.33495	25.9211	36.1361
0.4	1.28690	22.4467	28.3650	1.33270	25.6134	35.1742
0.5	1.29232	22.6788	28.6767	1.33045	25.3151	34.2626
0.6	1.29773	22.9085	28.9846	1.32819	25.0151	33.3840
0.7	1.30311	23.1407	29.3079	1.32593	24.7189	32.5607
0.8	1.30851	23.3755	29.6364	1.32371	24.4265	31.7756
0.9	1.31385	23.6180	29.9629	1.32144	24.1431	31.0181
1.0	1.31917	23.8580	30.3040	1.31917	23.8580	30.3040

Table 2: Variance values for FGRD, FRD and FLLD.

$\boldsymbol{\alpha}$	$V_L[X_\gamma^U(\alpha)]$			$V_U[X_\gamma^U(\alpha)]$		
	FGRD	**FRD**	**FLLD**	**FGRD**	**FRD**	**FLLD**
0.0	1.60000	2.9068	7.8586	2.16000	3.1347	7.16178
0.1	1.63950	2.9171	7.76397	2.14527	3.1222	7.14068
0.2	1.67928	2.9276	7.67112	2.13040	3.1099	7.12032
0.3	1.71977	2.9380	7.57849	2.11589	3.0974	7.09943
0.4	1.76044	2.9483	7.48901	2.10113	3.0850	7.08070
0.5	1.80171	2.9589	7.39831	2.08659	3.0728	7.06004
0.6	1.84325	2.9693	7.30924	2.07194	3.0604	7.04013
0.7	1.88540	2.9797	7.22037	2.05750	3.0480	7.01970
0.8	1.92794	2.9901	7.13450	2.04307	3.0356	7.00143
0.9	1.97098	3.0008	7.04597	2.02873	3.0236	6.97982
1.0	2.01428	3.0112	6.96179	2.01428	3.0112	6.96179

5 Testing of Hypothesis:

Testing of hypotheses is a procedure used to determine the degree of trial validity and provides a strategy for population-related decision-making, i.e., it conveys a method for acknowledging the consistency with which one can extrapolate experimental results from the sample under examine to the larger population that from which the population being studied was drawn. We start by defining a hypothesis, which is a specific statement of the population's parameters.

An example of such a hypothesis is H_0. Here, we define H_0 in the following manner:
$H_0 : \overline{\mu}_{Inf1} - \overline{\mu}_{Inf2} > 0$. There is significant difference in $\overline{\mu}_{\text{inf }1}$than $\overline{\mu}_{\text{inf }2}$.
$H_1 : \overline{\mu}_{Inf1} - \overline{\mu}_{Inf2} \leq 0$.

Test statistics for lower alpha values is defined by,

$$\tau_{Inf} = \left[\frac{\overline{\mu}_{Inf1} - \overline{\mu}_{Inf2}}{\sqrt{\frac{\delta^2_{Inf1}}{n_{Inf1}-1} + \frac{\delta^2_{Inf2}}{n_{Inf2}-1}}} \right],$$

$$\delta^2_{Inf1} = \left[\frac{\sum \left(\mu_{Inf} - \overline{\mu}_{Inf1} \right)}{n_{Inf} - 1} \right],$$

$$\text{and} \quad \delta^2_{Inf2} = \left[\frac{\sum \left(\mu_{Inf1} - \overline{\mu}_{Inf2} \right)}{n_{Inf2} - 1} \right].$$

Test statistics for upper alpha values is defined by,

$$\tau_{Sup} = \left[\frac{\overline{\mu}_{Sup1} - \overline{\mu}_{Sup2}}{\sqrt{\frac{\delta^2_{Sup1}}{n_{Sup1}-1} + \frac{\delta^2_{Sup2}}{n_{Sup2}-1}}} \right],$$

$$\delta^2_{Sup1} = \left[\frac{\sum \left(\mu_{Sup} - \overline{\mu}_{Sup1} \right)}{n_{Sup1} - 1} \right],$$

$$\text{and} \quad \delta^2_{Sup2} = \left[\frac{\sum \left(\mu_{Sup} - \overline{\mu}_{Sup2} \right)}{n_{Sup2} - 1} \right].$$

5.1 Lower fuzzy mean

Null hypothesis H_{GRR0} : The LFM in GRD and RD do not differ much from one another.

Alternative hypothesis H_{GRR1} : $\mathrm{H}_1 \neq \mathrm{H}_2$.

Null hypothesis H_{RLL0} : The LFM among RD and LLD does not significantly differ.

Alternative hypothesis H_{RLL1} : $\mathrm{H}_1 \neq \mathrm{H}_3$.

Null hypothesis H_{LLGR0} : The LFR from LLD and GRD is not significantly different from each other.

Alternative hypothesis H_{LLGR1} : $\mathrm{H}_2 \neq \mathrm{H}_3$.

The above all hypothesis results are shown in Table 3.

Table 3: Calculation of sample means and standard deviations of lower mean.

α	*X1*	*X2*	*X3*	*S1*S1*	*S2*S2*	*S3*S3*
0.0	1.264911	21.5576	27.183051	0.2208163	427.7740793	686.2278488
0.1	1.270433	21.7751	27.473111	0.2260365	436.8183600	701.5087787
0.2	1.275931	21.9997	27.759493	0.2312946	446.2571750	716.7610269
0.3	1.281444	22.2220	28.059990	0.2366278	455.6986784	732.9413730
0.4	1.286895	22.4467	28.365035	0.2419607	465.3425552	749.5513249
0.5	1.292323	22.6788	28.676713	0.2473302	475.4100552	766.7146681
0.6	1.297729	22.9085	28.984593	0.2527364	485.4795290	783.8596143
0.7	1.303112	23.1407	29.307900	0.2581778	495.7658496	802.0677126
0.8	1.308511	23.3755	29.636359	0.2636935	506.2770004	820.7800412
0.9	1.313849	23.6180	29.962946	0.2692043	517.2485976	839.5996514
1.0	1.319166	23.8580	30.304028	0.2747500	528.2228856	859.4822674

Calculated value of $|t_{GRR}| = 3.099255$, $|t_{RLL}| = 0.538719181$, $|t_{LLGR}| = 3.124980659$.

At a 5% level of significance, the tabulated value of $11 + 11 - 2 = 20$ d.f. is 2.080.

Calculated t_{GRR} bigger than Tabulated t_{GRR}.

The null hypothesis H_{GRR0} is rejected.

$11 + 11 - 2 = 20$ d. f. has a tabulated value of 2.080 at the 5% level of significance.

Calculated value of t_{RLL} is Less than the value of t_{RLL} in the table.

The null hypothesis H_{RLL0} is accepted.

At a 5% level of significance, the tabulated value of $11 + 11 - 2 = 20$ d.f. is 2.080.

Calculated value of t_{LLGR} is higher than the value of t_{LLGR} in the table.

We do accept the null theory H_{LLGR0}.

5.2 Upper fuzzy mean

Null hypothesis $H_{\omega LLU0}$: The UFM in GRD and RD are not significantly different from one another.

Alternative hypothesis $H_{\omega LLU1}$: $\mathrm{I}_1 \neq \mathrm{I}_2$.

Null hypothesis $H_{\omega\varepsilon U0}$: This UFM for RD and LLD are identical, and this is a significant distinction.

Alternative hypothesis $H_{\omega\varepsilon U1}$: $\mathrm{I}_1 \neq \mathrm{I}_3$.

Null hypothesis $H_{LL\varepsilon U0}$: Its UFM in the LLD and GRD are identical, and this is a significant distinction.

Alternative hypothesis $H_{LL\varepsilon U1}$: $\mathrm{I}_2 \neq \mathrm{I}_3$.

The above all hypothesis results are shown in Table 4.

Table 4: Calculation of sample means and standard deviations of upper mean.

α	Y1	Y2	Y3	S1*S1	S2*S2	S3*S3
0.0	1.341641	26.8625	39.373151	0.0604870	663.8403780	1421.293845
0.1	1.339403	26.5427	38.237943	0.0593912	647.4632921	1336.987744
0.2	1.337161	26.2328	37.150029	0.0583034	631.7883332	1258.612491
0.3	1.334953	25.9211	36.136114	0.0572420	616.2160817	1187.699334
0.4	1.332704	25.6134	35.174195	0.0561709	601.0342560	1122.323366
0.5	1.330451	25.3151	34.262621	0.0551080	586.4969933	1062.076879
0.6	1.328194	25.0151	33.383974	0.0540535	572.0563733	1005.579530
0.7	1.325934	24.7189	32.560702	0.0530077	557.9752623	954.0439573
0.8	1.323707	24.4265	31.775552	0.0519872	544.2469068	906.1576164
0.9	1.321439	24.1431	31.018128	0.0509581	531.1042885	861.1306683
1.0	1.319166	23.8580	30.304028	0.0499371	518.0449124	819.7300381

Calculated value of $|t_{GRRU}| = 3.442251$, $|t_{RLLU}| = 0.778690192$, $|t_{LLGRU}| = 3.501450021$.

For the $11 + 11 - 2 = 20$ d.f., the tabulated value of $t_{\omega LLU}$ is 2.080 at the 5% level of significance.

Value of t_{GRRU} higher than calculated value of t_{GRRU} in the table.

Rejected is the null hypothesis H_{GRRU0}.

At a 5% level of significance, the tabulated value of $11 + 11 - 2 = 20$ d.f. is 2.080.

Calculated value of t_{RLLU} is bigger than the tabulated value of t_{RLLU}.

We reject the null hypothesis H_{RLLU0}.

$11 + 11 - 2 = 20$ d.f. has a tabulated value of 2.080 at the 5% level of significance.

Calculated value of $t_{LLGRU} >$ tabulated value of t_{LLGRU}.

We do not accept the null hypothesis H_{LLGRU0}.

5.3 Lower fuzzy variance

Null hypothesis H_{GRRV0} : The LFV in GRD and RD do not differ much from one another.

Alternative hypothesis H_{GRRV1} : $\mathrm{H}_1 \neq \mathrm{H}_2$.

Null hypothesis H_{RLLV0} : The LFV among RD and LLD does not significantly differ.

Alternative hypothesis H_{RLLV1} : $\mathrm{H}_1 \neq \mathrm{H}_3$.

Null hypothesis H_{LLGRV0} : The LFV from LLD and GRD is not significantly different from each other.

Alternative hypothesis H_{LLGRV1} : $\mathrm{H}_2 \neq \mathrm{H}_3$.

The above all hypothesis results are shown in Table 5.

Table 5: Calculation of sample means and standard deviations of lower variance.

α	*X1*	*X2*	*X3*	*S1*S1*	*S2*S2*	*S3*S3*
0.0	1.600000	2.9068	7.858603	0.6480250	4.12861761	47.2175535
0.1	1.639501	2.9171	7.763972	0.7131819	4.17058084	45.9259941
0.2	1.679282	2.9276	7.671115	0.7819547	4.21357729	44.6760565
0.3	1.719773	2.9380	7.578492	0.8552051	4.25638161	43.4464485
0.4	1.760436	2.9483	7.489014	0.9320667	4.29898756	42.2748857
0.5	1.801705	2.9589	7.398306	1.0134550	4.34305600	41.1035624
0.6	1.843247	2.9693	7.309237	1.0988218	4.38651136	39.9694162
0.7	1.885400	2.9797	7.220369	1.1889722	4.43018304	38.8536424
0.8	1.927936	2.9901	7.134495	1.2835440	4.47407104	37.7904653
0.9	1.970976	3.0008	7.045971	1.3829196	4.51945081	36.7099178
1.0	2.014283	3.0112	6.961789	1.4866510	4.56377769	35.6969086

Calculated value of $|t_{GRRV}| = 1.57484$, $|t_{RLLV}| = 2.081386209$, $|t_{LLGRV}| = 2.723051839$.

At a 5% level of significance, the tabulated value of $11 + 11 - 2 = 20$, d.f. is 2.080.

Calculated t_{GRRV} less than valuet_{GRRV}'s tabulated.

The null hypothesis H_{GRRV0} is acceptable.

$11 + 11 - 2 = 20$, d.f. has a tabulated value of 2.080 at the 5% level of significance.

Calculated value of t_{RLLV} is bigger than the value of t_{RLLV} in the table.

The null hypothesis H_{RLLV0} is rejected.

At a 5% level of significance, the tabulated value of $11 + 11 - 2 = 20$, d.f. is 2.080.

Calculated value of t_{LLGRV} is higher than the value of t_{LLGRV} in the table.

We do not accept the null theory H_{LLGRV0}.

5.4 Upper fuzzy variance

Null hypothesis H_{GRRVL0} : The UFV in GRD and RD are not significantly different from one another.

Alternative hypothesis H_{GRRVL1} : $\mathrm{I}_1 \neq \mathrm{I}_2$.

Null hypothesis H_{RLLVL0} : This UFV for RD and LLD are identical, and this is a significant distinction.

Alternative hypothesis H_{RLLVL1} : $\mathrm{I}_1 \neq \mathrm{I}_3$.

Null hypothesis $H_{LLGRVL0}$: Its UFV in the LLD and GRD are identical, and this is a significant distinction.

Alternative hypothesis $H_{LLGRVL1}$: $\mathrm{I}_2 \neq \mathrm{I}_3$.

The above all hypothesis results are shown in Table 6.

Table 6: Calculation of sample means and standard deviations of upper variance.

α	*Y1*	*Y2*	*Y3*	*S1*S1*	*S2*S2*	*S3*S3*
0.0	2.159999	3.1347	7.161784	1.1327324	4.15059129	30.12565205
0.1	2.145265	3.1222	7.140681	1.1015867	4.09981504	29.89444199
0.2	2.130402	3.1099	7.120316	1.0706082	4.05015625	29.67216215
0.3	2.115888	3.0974	7.099433	1.0407836	4.00000000	29.44508983
0.4	2.101126	3.0850	7.080699	1.0108814	3.95055376	29.24212694
0.5	2.086594	3.0728	7.060039	0.9818709	3.90220516	29.01911179
0.6	2.071936	3.0604	7.040133	0.9530367	3.85336900	28.80504322
0.7	2.057503	3.0480	7.019698	0.9250650	3.80484036	28.58611017
0.8	2.043065	3.0356	7.001431	0.8975004	3.75661924	28.39111125
0.9	2.028734	3.0236	6.979818	0.8705524	3.71024644	28.16125593
1.0	2.014283	3.0112	6.961789	0.8437947	3.66263044	27.97023134

Calculated value of $|t_{GRRVL}| = 1.551309$, $|t_{RLLVL}| = 2.417177098$, $|t_{LLGRVL}| = 3.158069152$.

For the $11 + 11 - 2 = 20$ d.f., the tabulated value of $t_{\omega LLU}$ is 2.080 at the 5% level of significance.

Value of t_{GRRVL} less than calculated value of t_{GRRVL} in the table.

Accepted is the null hypothesis H_{GRRVL0}.

At a 5% level of significance, the tabulated value of $11 + 11 - 2 = 20$ d.f. is 2.080.

Calculated value of t_{RLLVL} is bigger than the tabulated value of t_{RLLVL}.

We reject the null hypothesis H_{RLLVL0}.

$11 + 11 - 2 = 20$ d.f. has a tabulated value of 2.080 at the 5% level of significance.

Calculated value of $t_{LLGRVL} >$ Tabulated value of t_{LLGRVL}.

We do not accept the null hypothesis $H_{LLGRVL0}$.

Table 7 and 8 discussed about null and alternative hypothesis of the upper fuzzy variance.

Table 7: Paired sample $t-$test for fuzzy mean model for the effect of corticosterone.

Test	Calculated value		Table value	Hypothesis		d. f	Result
	Lower fuzzy mean	Upper fuzzy mean		Lower fuzzy mean	Upper fuzzy mean		
t_{GRR}	3.099255	3.442251	2.086	Rejected	Rejected	5%	The fuzzy mean in the GRD and the Rayleigh distribution differ significantly from one another.
t_{RLL}	0.5387192	0.7786902	2.086	Accepted	Accepted		The fuzzy mean in the Rayleigh distribution and the Log-Logistic distribution do not differ significantly.
t_{LLGR}	3.124980	3.501450	2.086	Rejected	Rejected		The Log-Logistic distribution's fuzzy mean and the GRD differ significantly.
t_{GRR}	3.099255	3.442251	2.845	Rejected	Rejected	1%	The fuzzy mean in the generalized Rayleigh l distribution and the Rayleigh distribution significantly differ from one another.
t_{RLL}	0.5387192	0.7786902	2.845	Accepted	Accepted		The fuzzy mean in the GRD and the Rayleigh distribution do not differ significantly from one another.
t_{LLGR}	3.124980	3.501450	2.845	Rejected	Rejected		The fuzzy mean in the Log-Logistic distribution and the distribution are very different from one another.

Table 8: Paired sample t-test for fuzzy Variance Model for the effect of Corticosterone

Generalized Rayleigh test	Calculated value		Table value	Hypothesis		d. f	Result
	Lower fuzzy variance	Upper fuzzy variance		Lower fuzzy variance	Upper fuzzy variance		
t_{GRR}	1.57484	1.551309	2.086	Accepted	Accepted	5%	The Fuzzy Reliability in the GRD and the Rayleigh distribution do not differ significantly from one another.
t_{RLL}	2.081386	2.417177	2.086	Accepted	Rejected		The Fuzzy Reliability in the Log-Logistic distribution and the Rayleigh distribution differ significantly.
t_{LLGR}	2.7230519	3.15807	2.086	Rejected	Rejected		The GRD's fuzzy reliability and the Log-Logistic distribution differ significantly.
t_{GRR}	1.57484	1.551309	2.845	Accepted	Accepted	1%	The Fuzzy Reliability in the GRD and the Rayleigh distribution do not significantly differ from one another.
t_{RLL}	2.081386	2.417177	2.845	Accepted	Accepted		The Fuzzy Reliability in the Log-Logistic distribution and the Rayleigh distribution do not differ significantly from one another.
t_{LLGR}	2.7230519	3.15807	2.845	Accepted	Rejected		The Fuzzy Reliability in the GRD and the Log-Logistic distribution are very different from one another.

6 Conclusion

By estimating both the variance and the mean of FGRD, FRD and FLLD, we were able to successfully create the fuzzy model to calculate the effect of Corticosterone. Upper alpha cuts result in higher mean values, and for lower alpha cuts result in lower mean values. The results of the testing of the hypothesis reveal a substantial difference between FGRD, FRD, and FLLD. For assessing the impact of Corticosterone, FRD and FLLD work effectively. In the current study, we covered fuzzy mathematical models for the GRD, Rayleigh distribution, and Log-Logistic distribution. To elucidate the impact of corticosterone, the GRD, Rayleigh distribution, and Log-Logistic distribution are utilized. Moreover, a comparison utilizing hypothesis testing has been created to compare the anticipated degrees of respiratory alterations subsequent to corticosterone administration for different distribution models.

Acknowledgement The researcher would like to acknowledge the cooperation given by all the participants of this study, the supervisory committee, and the sponsors, namely the sponsorship department, Vel Tech High Tech DR Ragarajan DR Sakunthala Engineering College, India.

Conflicts of Interest There is no conflict of interest, the author argues.

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