International Journal of Computational Research and Development (IJCRD)
Impact Factor: 4.775, ISSN (Online): 2456 - 3137
(www.dvpublication.com) Volume 2, Issue 2, 2017

A COMPARATIVE MATHEMATICAL ANALYSIS OF FUZZY MODELS FOR THE EFFECT OF OXYTOCIN

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Cite This Article: A. Venkatesh, R. Manikandan & K. Vetrivel, "A Comparative Mathematical Analysis of Fuzzy Models for the Effect of Oxytocin", International Journal of Computational Research and Development, Volume 2, Issue 2, Page Number 40-46, 2017.

Abstract:

In this study we discussed the various fuzzy mathematical models using generalized gamma distribution, log-logistic distribution, generalized Rayleigh distribution and Rayleigh distributionfor the effect of oxytocin.Also a comparative analysis is established using testing of hypothesis between the expected values of respiratory changes after the administration of oxytocinfor different distribution models.

Key Words: Hypothesis Testing, Oxytocin

1. Introduction:

The importance of the techniques used in a statistical investigation rest on extremely on the presumed probability model or distribution.The purpose of statistical interpretation is to draw decisionsabout a population on the source of data acquired from a sampleof that population. Hypothesis testing is the procedure usedto assess the strength of evidence from the sample andprovides a basis for making choices related to thepopulation, i.e., it provides a technique for understanding howconsistently one can generalizeexperiential findings in a sampleunder study to the higher population from which the samplewas taken.A method using parametric testing statistical hypotheses for fuzzy randomvariables proposed by Gholamreza Hesamian, Mehdi Sham [3]. Fuzzy hypothesis testing using likelihood ratio statistic was developed by Shima Yosefi etc [11]. A new approach for testing fuzzy hypotehesis based on fuzzy data was discussed by Mohsen Arefi, S. Mahmoud Taheri [7]. A classical one-sided hypothesis testingproblem about the population mean for intervaldatawas conversed by Przemysław etc. [10]. Olgierd Hryniewicz etc. [9] proposed a methodology for Bayes statistical decision analysis is to compare fuzzy risks related to considered decisions for the case of reliability using weibull distribution.

Oxytocin is a mammalian neurohypophysial nonapeptide hormone secreted by the posterior pituitary gland and shown to play important roles in various regulatory functions. The haemodynamic effects of an oxytocin bolus involveof complete vasodilatation, with hypotension, tachycardia,and an intensification in cardiac output and respiratory blood vesselpressure, causing in brief hypotension and tachycardia ina dose-dependent manner.World Health Organization (WHO) defines primary postpartumhemorrhage (PPH) as blood loss of greater than or equal to 1000 ml followingcesarean section (CS) [4]. It accounts for one-quarter of themajor direct causes of maternal deaths globally [12], while itrises up to nearly one-third of mortalities in Africa and Asia[5]. The risk of postpartum complications in women whoreceived a CS was higher than that in women who underwent avaginal delivery (VD) and vaginal birth after cesarean section(VBAC) [2,6]. The incidence of PPH has been reported to be3.9% in women delivered vaginally and reaches 7.9% after CS [8].

In this paper organized as follows, in section 2 we presented the notations involved in this paper. In section 3 we introduced the different kinds of fuzzy mathematical model using the generalized gamma distribution (GGD), log-logistic distribution (LLD), generalized Rayleigh distirbution(GRD) and Rayleigh distribution (RD). In section 4 we were using the above mentioned models in an application to find the finding effect of oxytocin by finding the mean and variance values. In section 5 using testing of hypothesis we compare the mean and varaince values of the various models. In section 6 a breif conclusion is delivered.

2. Notations:

λ	– Scale parameter of GGD
μ, φ	– Shape parameter of GGD
η	– Scale Parameter LLD
ψ	– Shape Parameter LLD
β	– Scale parameter of RD and GRD
χ	–Shape parameter GRD
$E(X)$	– Mean value of X
$V(X)$	– Variance value of X

$\overline{E}(X)$ – Fuzzy mean value of X

$\overline{V}(X)$ – Fuzzy variance value of X

3. Fuzzy Mathematical Models:

3.1 Fuzzy Generalized Gamma Distribution Model: The probability density function (p.d.f.) of random variable (r.v.) X follows GGD is given by $f(x)=\frac{\lambda x^{\lambda\varphi-1}e^{-\left(x/\mu\right)^{\lambda}}}{\mu^{\lambda\varphi}\Gamma(\varphi)},\ x>0$ where λ – is the scale parameter, μ and φ are the shape parameters.

The expected value and variance value of X are given by

$$E[X]=\frac{\mu\Gamma\left(\varphi+1/\lambda\right)}{\Gamma\varphi},\quad V[X]=\mu^{2}\left(\frac{\Gamma\left(\varphi+2/\lambda\right)}{\Gamma\varphi}-\left(\frac{\Gamma\left(\varphi+1/\lambda\right)}{\Gamma\varphi}\right)^{2}\right).$$

A r.v. X follows Fuzzy Generalized Gamma distribution (FGGD) with fuzzy parameter $\overline{\lambda},\overline{\mu},\overline{\varphi}$ is symbolized by $X\sim FGGD\left(x;\overline{\lambda},\overline{\mu},\overline{\varphi}\right)$. The expected value of $X\sim FGGD\left(x;\overline{\lambda},\overline{\mu},\overline{\varphi}\right)$ is given by

$$\overline{E}(X)=\left\{E(X)[\alpha],\mu_{E(X)}\middle|E(X)[\alpha]=E_{L}(X)[\alpha],\ E_{U}(X)[\alpha],\mu_{E(X)}=\alpha\right\}$$

$$E_{L}(X)[\alpha]=\inf.\left\{E(X)\middle|\ \lambda\in\overline{\lambda}(\alpha),\mu\in\overline{\mu}(\alpha),\varphi\in\overline{\varphi}(\alpha)\right\}$$

$$E_{U}(X)[\alpha]=\sup.\left\{E(X)\middle|\lambda\in\overline{\lambda}(\alpha),\mu\in\overline{\mu}(\alpha),\varphi\in\overline{\varphi}(\alpha)\right\}$$

$$\overline{E}[X]=\frac{\overline{\mu}\Gamma\left(\overline{\varphi}+1/\overline{\lambda}\right)}{\Gamma\overline{\varphi}},\ \ \lambda\in\overline{\lambda}(\alpha),\mu\in\overline{\mu}(\alpha),\varphi\in\overline{\varphi}(\alpha).$$

The variance value of $X\sim FGGD\left(x;\overline{\lambda},\overline{\mu},\overline{\varphi}\right)$ is given by

$$\overline{V}(X)=\left\{V(X)[\alpha],\mu_{V(X)}\middle|V(X)[\alpha]=V_{L}(X)[\alpha],\ V_{U}(X)[\alpha],\mu_{V(X)}=\alpha\right\}$$

$$V_{L}(X)[\alpha]=\inf\left\{V(X)\middle|\lambda\in\overline{\lambda}(\alpha),\mu\in\overline{\mu}(\alpha),\varphi\in\overline{\varphi}(\alpha)\right\}$$

$$V_{U}(X)[\alpha]=\sup\left\{V(X)\middle|\ \lambda\in\overline{\lambda}(\alpha),\mu\in\overline{\mu}(\alpha),\varphi\in\overline{\varphi}(\alpha)\right\}$$

$$V[X]=\overline{\mu}^{2}\left(\frac{\Gamma\left(\overline{\varphi}+2/\overline{\lambda}\right)}{\Gamma\overline{\varphi}}-\left(\frac{\Gamma\left(\overline{\varphi}+1/\overline{\lambda}\right)}{\Gamma\overline{\varphi}}\right)^{2}\right)$$

3.2 Fuzzy Log-Logistic Distribution Model: A r.v. X follows log-logistic distribution with scale and shape parameter η , ψ respectively is denoted by $X\sim LLD(\eta,\psi)$. The p.d.f. of $X\sim LLD(\eta,\psi)$ is

$$f(x;\eta,\psi)=\frac{\left(\psi/\eta\right)\left(x/\eta\right)^{\psi-1}}{\left(1+\left(x/\eta\right)^{\psi}\right)^{2}}\quad \eta>0,\ \psi\geq 1.$$

The expected value and the variance of LLD are given by

$$E(X)=\frac{\eta\left(\pi/\psi\right)}{\sin\left(\pi/\psi\right)},\ \ V[X]=\frac{\eta^{2}\left(\left(2\pi/\psi\right)\sin 2\left(\pi/\psi\right)-\left(\pi/\psi\right)^{2}\right)}{\sin^{2}\left(\pi/\psi\right)}$$ respectively.

A r.v. X follows fuzzy log-logistic distribution (FLLD) with the fuzzy numbers $\overline{\eta},\overline{\psi}$ is indicated by $X\sim FLLD(\overline{\eta},\overline{\psi})$. The expected value for $X\sim FLLD(\overline{\eta},\overline{\psi})$ is

$$\bar{E}(X)=\left\{E(X)[\alpha],\mu_{E(X)}\middle|E(X)[\alpha]=E_L(X)[\alpha],\ E_U(X)[\alpha],\mu_{E(X)}=\alpha\right\}$$

$$E_L(X)[\alpha]=\inf.\left\{E(X)\middle|\eta\in\bar{\eta}(\alpha),\ \bar{\psi}\in\bar{\psi}(\alpha)\right\}$$

$$E_U(X)[\alpha]=\sup.\left\{E(X)\middle|\eta\in\bar{\eta}(\alpha),\ \bar{\psi}\in\bar{\psi}(\alpha)\right\}$$

$$\bar{E}(X)=\frac{\bar{\eta}\left(\pi/\psi\right)}{\sin\left(\pi/\psi\right)},\ \eta\in\bar{\eta}(\alpha),\ \bar{\psi}\in\bar{\psi}(\alpha).$$

The variance values of $X\sim FLLD(\bar{\eta},\bar{\psi})$ is

$$\bar{V}(X)=\left\{V(X)[\alpha],\mu_{V(X)}\middle|V(X)[\alpha]=V_L(X)[\alpha],V_U(X)[\alpha],\mu_{V(X)}=\alpha\right\}$$

$$V_L(X)[\alpha]=\inf.\left\{V(X)\middle|\eta\in\bar{\eta}(\alpha),\ \bar{\psi}\in\bar{\psi}(\alpha)\right\}$$

$$V_U(X)[\alpha]=\sup.\left\{V(X)\middle|\eta\in\bar{\eta}(\alpha),\ \bar{\psi}\in\bar{\psi}(\alpha)\right\}$$

$$V[X]=\frac{\bar{\eta}^2\left(\left(2\pi/\psi\right)\sin 2\left(\pi/\psi\right)-\left(\pi/\psi\right)^2\right)}{\sin^2\left(\pi/\psi\right)},\ \bar{\eta}\in\bar{\eta}(\alpha),\ \psi\in\bar{\psi}(\alpha).$$

3.3 Fuzzy Rayleigh Distribution Model: The p.d.f.of a r.v. X follows RD is given by $f(x)=\frac{x}{\beta^2}e^{-\frac{1}{2}\left(\frac{x}{\beta}\right)^2}$, where $0\le x\le\infty,\ \beta>0$.

The mean and variance of RD is $E(X)=\beta\sqrt{\frac{\pi}{2}}$ and $V(X)=\beta^2\left(2-\frac{\pi}{2}\right)$ respectively.

A r.v. X follows Fuzzy Rayleigh distribution is denoted by $X\sim FRD(x;\bar{\beta})$ with fuzzy parameter $\bar{\beta}$.

The fuzzy p.d.f. of a random variable X follows Fuzzy Rayleigh distribution
The Mean of FRD distribution is given by

$$\bar{E}(X)=\left\{E(X)[\alpha],\mu_{E(X)}\middle|E(X)[\alpha]=E_L(X)[\alpha],\ E_U(X)[\alpha],\mu_{E(X)}=\alpha\right\}$$

$$E_L(X)[\alpha]=\inf\left\{E(X)\middle|\beta\in\bar{\beta}(\alpha)\right\},\ \ E_U(X)[\alpha]=\sup\left\{E(X)\middle|\beta\in\bar{\beta}(\alpha)\right\}$$

$$\bar{E}(X)=\bar{\beta}\sqrt{\frac{\pi}{2}},\ \bar{\beta}\in\bar{\beta}(\alpha).$$

The fuzzy variance is defined as follows

$$\bar{V}(X)=\left\{V(X)[\alpha],\mu_{V(X)}\middle|V(X)[\alpha]=V_L(X)[\alpha],V_U(X)[\alpha],\mu_{V(X)}=\alpha\right\}$$

$$V_L(X)[\alpha]=\inf\left\{V(X)\middle|\beta\in\bar{\beta}(\alpha)\right\},V_U(X)[\alpha]=\sup\left\{V(X)\middle|\beta\in\bar{\beta}(\alpha)\right\}$$

$$\bar{V}(X)=\left(\bar{\beta}\right)^2\left(2-\frac{\pi}{2}\right)$$

3.4 Fuzzy Generalized Rayleigh Distribution: A r.v. X follows the GRD has p.d.f. of the form $f(x:\chi,\beta)=\frac{2}{\Gamma(\chi+1)\beta^{\chi+1}}x^{2\beta+1}e^{\frac{x^2}{\chi}},x>0$, where $\chi\ge 0$ is the shape parameter and $\beta>0$ is the scale parameter. The expected value and variance of GRD are

$E(X)=\frac{\Gamma\left(\chi+\frac{3}{2}\right)}{\Gamma(\chi+1)}\sqrt{\beta}$ and $V(X)=\left((\chi+1)-\left(\frac{\Gamma\left(\chi+\frac{3}{2}\right)}{\Gamma(\chi+1)}\right)^2\right)\beta$ respectively.

If a r.v. X follows fuzzy generalized Rayleigh Distribution is denoted by $X \sim FGRD\left(x:\overline{\chi},\overline{\beta}\right)$ where $\overline{\beta},\ \overline{\chi}$ are fuzzy parameters.

The expected value of $X \sim FGRD\left(x;\overline{\beta},\overline{\chi}\right)$ is given by

$$\overline{E}(X)=\left\{E(X)[\alpha],\mu_{E(X)}\middle|E(X)[\alpha]=E_L(X)[\alpha],\,E_U(X)[\alpha],\mu_{E(X)}=\alpha\right\}$$

$$E_L(X)[\alpha]=\inf.\left\{E(X)\middle|\overline{\chi}\in\overline{\chi}(\alpha),\overline{\beta}\in\overline{\beta}(\alpha)\right\},$$

$$E_U(X)[\alpha]=\sup.\left\{E(X)\middle|\overline{\chi}\in\overline{\chi}(\alpha),\overline{\beta}\in\overline{\beta}(\alpha)\right\}$$

$$\overline{E}[X]=\frac{\Gamma\left(\overline{\chi}+\frac{3}{2}\right)}{\Gamma\left(\overline{\chi}+1\right)}\sqrt{\overline{\beta}},\ \ \overline{\chi}\in\overline{\chi}(\alpha),\,\overline{\beta}\in\overline{\beta}(\alpha).$$

The variance value of $X \sim FGRD\left(x;\overline{\lambda},\overline{\mu},\overline{\varphi}\right)$ is given by

$$\overline{V}(X)=\left\{V(X)[\alpha],\mu_{V(X)}\middle|V(X)[\alpha]=V_L(X)[\alpha],\,V_U(X)[\alpha],\mu_{V(X)}=\alpha\right\}$$

$$V_L(X)[\alpha]=\inf\left\{V(X)\middle|\overline{\chi}\in\overline{\chi}(\alpha),\overline{\beta}\in\overline{\beta}(\alpha)\right\},$$

$$V_U(X)[\alpha]=\sup\left\{V(X)\middle|\overline{\chi}\in\overline{\chi}(\alpha),\overline{\beta}\in\overline{\beta}(\alpha)\right\}.$$

$$\overline{V}[X]=\left(\left(\overline{\chi}+1\right)-\left(\frac{\Gamma\left(\overline{\chi}+\frac{3}{2}\right)}{\Gamma\left(\overline{\chi}+1\right)}\right)^2\right)\overline{\beta},\ \ \overline{\chi}\in\overline{\chi}(\alpha),\,\overline{\beta}\in\overline{\beta}(\alpha),.$$

Consider a random variable X follows fuzzy log logistic distribution (FLLD) with the fuzzy numbers $\overline{\eta},\ \overline{\psi}$ as parameters is indicated by $X \sim FLLD(\overline{\eta},\overline{\psi})$.

4. Results and Application:

Consider a trail conducted by Ahmed [1], for prevention of postpartum hemorrhage (PPH) after cesarean section by administrating the study drug oxytocin. The study was conducted on 150 patients after fetal extraction. The respiratory changes were given in the figure 1. Based on this study the parameters of GGD λ,μ,φ are 1.0272, 71.316, 0.3455 respectively, the LLD parameters η,ψ are and 10.986, 21.107 respectively, the parameters of GRD β,χ are , 4.0012, 16.932respectively and RD parameter β is 17.5530.

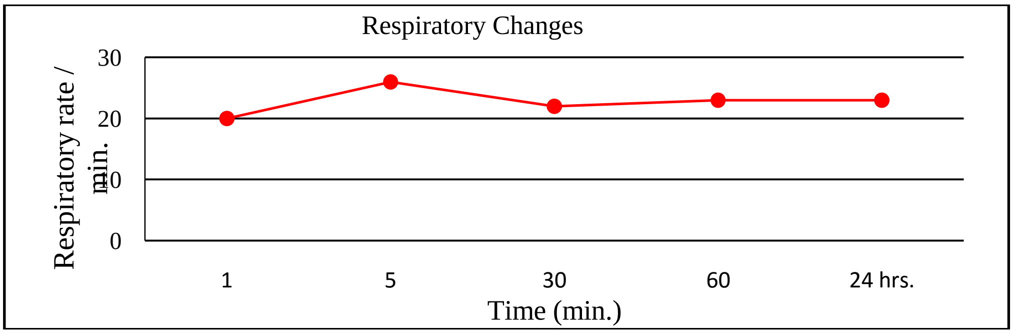

Figure 4.1: Respiratory rate per minute after administration of oxytocin

The corresponding fuzzy triangular numbers of the GGD parameters are $\bar{\lambda} = [0.9601, 1.0272, 1.1118]$, $\bar{\mu} = [70.0341, 71.3160, 72.6905]$, $\bar{\varphi} = [0.3428, 0.3455, 0.3500]$. The corresponding α –cuts are $\bar{\mu}(\alpha) = [0.9601 + 0.0671\alpha, 1.1118 - 0.0846\alpha]$, $\bar{\varphi}(\alpha) = [7.0341 + 1.2819\alpha, 72.6905 - 1.3745\alpha]$ and $\bar{\varphi}(\alpha) = [0.3428 + 0.0027\alpha, 0.3500 - 0.0045\alpha]$.

The corresponding fuzzy triangular numbers of the LLD parameters are $\bar{\eta} = [9.9623, 10.860, 12.0283]$, $\bar{\psi} = [19.8328, 21.1070, 22.4751]$ and the corresponding α –cuts are $\bar{\eta}(\alpha) = [9.9623 + 1.0237\alpha, 12.0283 - 1.0423\alpha]$, $\bar{\psi}(\alpha) = [19.8328 + 1.2742\alpha, 22.4751 - 1.3681\alpha]$.

The corresponding fuzzy triangular numbers of the GRD parameters are $\bar{\beta} = [15.9023, 16.9320, 17.9806]$, $\bar{\chi} = [3.0589, 4.0012, 4.8743]$. The corresponding α –cuts are $\bar{\beta}(\alpha) = [15.9023 + 1.0297\alpha, 17.9806 - 1.0486\alpha]$ $\bar{\chi}(\alpha) = [3.0589 + 0.9423\alpha, 4.8743 - 0.8731\alpha]$.

The corresponding fuzzy triangular number for RD parameter is $\bar{\beta} = [16.7484, 17.5530, 18.2982]$ and the corresponding α –cut is $\bar{\beta}(\alpha) = [16.7484 + 0.8046\alpha, 18.2982 - 0.7452\alpha]$.

Table 4.1: Mean values for FLLD, FGGD, FGRD, FRD

α	$E_L(X)[\alpha]$				$E_U(X)[\alpha]$			
	FLLD	**FGGD**	**FGRD**	**FRD**	**FLLD**	**FGGD**	**FGRD**	**FRD**
0	10.0041	23.9086	7.1375	20.9910	12.0676	25.8804	9.5555	22.9334
0.1	10.1063	23.9856	7.2689	21.0918	11.9635	25.7596	9.4429	22.8400
0.2	10.2086	24.0637	7.3994	21.1927	11.8594	25.6400	9.3301	22.7466
0.3	10.3109	24.1429	7.5288	21.2935	11.7553	25.5215	9.2168	22.6532
0.4	10.4131	24.2233	7.6574	21.3944	11.6512	25.4042	9.1031	22.5598
0.5	10.5154	24.3047	7.7851	21.4952	11.5471	25.2881	8.9890	22.4664
0.6	10.6176	24.3871	7.9119	21.5961	11.4430	25.1732	8.8745	22.3730
0.7	10.7199	24.4706	8.0380	21.6969	11.3389	25.0596	8.7595	22.2796
0.8	10.8222	24.5550	8.1632	21.7977	11.2348	24.9473	8.6441	22.1862
0.9	10.9244	24.6404	8.2878	21.8986	11.1308	24.8363	8.5281	22.0928
1	11.0267	24.7268	8.4117	21.9994	11.0267	24.7268	8.4117	21.9994

Table 4.2: Variance values for FLLD, FGGD, FGRD, FRD

α	$V_L(X)[\alpha]$				$V_U(X)[\alpha]$			
	FLLD	**FGGD**	**FGRD**	**FRD**	**FLLD**	**FGGD**	**FGRD**	**FRD**
0	98.4370	1810.3903	0.7590	120.3955	143.7550	1555.6726	1.2104	143.7077
0.1	100.4807	1795.0080	0.7824	121.5550	141.2635	1565.9066	1.1887	142.5396
0.2	102.5454	1780.1480	0.8058	122.7201	138.7937	1576.5268	1.1670	141.3763
0.3	104.6311	1765.7889	0.8292	123.8908	136.3457	1587.5506	1.1453	140.2177
0.4	106.7378	1751.9103	0.8527	125.0670	133.9195	1598.9964	1.1235	139.0638
0.5	108.8656	1738.4929	0.8761	126.2488	131.5151	1610.8838	1.1018	137.9148
0.6	111.0144	1725.5183	0.8995	127.4361	129.1324	1623.2334	1.0801	136.7705
0.7	113.1841	1712.9691	0.9229	128.6290	126.7715	1636.0671	1.0584	135.6310
0.8	115.3749	1700.8286	0.9464	129.8274	124.4324	1649.4080	1.0367	134.4962
0.9	117.5867	1689.0810	0.9698	131.0314	122.1151	1663.2808	1.0149	133.3662
1	119.8195	1677.7114	0.9932	132.2410	119.8195	1677.7114	0.9932	132.2410

4.1 Testing of Hypothesis: Hypothesis testing is the process used to extent the strength of validation from the trial and offers a plan for making decisionsrelated to the population, i.e., it conveys a technique for accepting how consistently one can deduceexperimental findings in a sample under study to the greater population from which the sample was drawn. We first define a hypothesis – a certaindeclaration of the population parameters. Such a hypothesis denoted by H_0. Here we define the as H_0 follows,

H_0: $\overline{\mu_1} - \overline{\mu_2} > 0$ there is significant difference in μ_1 than μ_2

H_1: $\overline{\mu_1} \leq \overline{\mu_2}$.

Test statistic for lower alpha values is defined by

$$t_{\min} = \left[\frac{\bar{\mu}_{\min}\sqrt{n}}{S_{\min}} \right]$$

$$S_{\min}^2 = \left[\frac{\sum\left(\mu_{\min} - \bar{\mu}_{\min}\right)^2}{n-1} \right] \text{ and } S_{\min} = \sqrt{S_{\min}^2}\,.$$

Test statistic for upper alpha values is defined by

$$t_{\max} = \left[\frac{\bar{\mu}_{\max}\sqrt{n}}{S_{\max}} \right]$$

$$S_{\max}^2 = \left[\frac{\sum\left(\mu_{\max} - \bar{\mu}_{\max}\right)^2}{n-1} \right] \text{ and } S_{\sup} = \sqrt{S_{\sup}^2}\,.$$

a) For FLLD and FGRD $\bar{\mu}_{min} = \bar{E}_{L(FLLD)} - \bar{E}_{L(FGRD)}$ and $\bar{\mu}_{\max} = \bar{E}_{U(FLLD)} - \bar{E}_{U(FGRD)}$

b) For FGGD and FGRD $\bar{\mu}_{min} = \bar{E}_{L(FGGD)} - \bar{E}_{L(FGRD)}$ and $\bar{\mu}_{\max} = \bar{E}_{U(FGGD)} - \bar{E}_{U(FGRD)}$

c) For FRD and FGRD $\bar{\mu}_{min} = \bar{E}_{L(FRD)} - \bar{E}_{L(FGRD)}$ and $\bar{\mu}_{\max} = \bar{E}_{U(FRD)} - \bar{E}_{U(FGRD)}$

d) For FGGD and FLLD $\bar{\mu}_{min} = \bar{E}_{L(FGGD)} - \bar{E}_{L(FLLD)}$ and $\bar{\mu}_{\max} = \bar{E}_{U(FGGD)} - \bar{E}_{U(FLLD)}$

e) For FRD and FLLD $\bar{\mu}_{min} = \bar{E}_{L(FRD)} - \bar{E}_{L(FLLD)}$ and $\bar{\mu}_{\max} = \bar{E}_{U(FRD)} - \bar{E}_{U(FLLD)}$

f) For FGGD and FRD $\bar{\mu}_{min} = \bar{E}_{L(FGGD)} - \bar{E}_{L(FRD)}$ and $\bar{\mu}_{\max} = \bar{E}_{U(FGGD)} - \bar{E}_{U(FRD)}$

Now we applying the paired sample t-test for the values in table 4.1.

Table 4.3: Testing of Hypothesis Results for Fuzzy Mean values

Paired Samples Test									
S. No.	**Paired Distributions**	**Paired Differences**					**t**	**df**	**Sig. (2-tailed)**
		Mean	**Std. Deviation**	**Std. Error Mean**	**95% Confidence Interval of the Difference**				
					Lower	**Upper**			
1	FLLDLower – FGRDLower	2.73	0.08	0.03	2.68	2.79	108.77	10	.000
2	FGGDLower – FGRDLower	16.53	0.15	0.05	16.43	16.63	362.45	10	.000
3	FRDLower – FGRDLower	13.71	0.09	0.03	13.66	13.77	516.44	10	.000
4	FGGDLower – FLLDLower	13.79	0.07	0.02	13.75	13.84	673.97	10	.000
5	FRDLower – FLLDLower	10.98	0.00	0.00	10.98	10.98	7750.17	10	.000
6	FGGDLower – FRDLower	2.81	0.06	0.02	2.77	2.86	147.72	10	.000
7	FLLDUpper – FGRDUpper	2.56	0.03	0.01	2.54	2.58	248.89	10	.000
8	FGGDUpper – FGRDUpper	16.31	0.01	0.00	16.30	16.31	6354.15	10	.000
9	FRDUpper – FGRDUpper	13.48	0.07	0.02	13.43	13.53	642.81	10	.000
10	FGGDUpper – FLLDUpper	13.75	0.04	0.01	13.72	13.77	1201.15	10	.000
11	FRDUpper – FLLDUpper	10.92	0.04	0.01	10.90	10.94	1021.25	10	.000
12	FGGDUpper – FRDUpper	2.83	0.07	0.02	2.78	2.88	128.11	10	.000

- ✓ If Sig. value > .05 – $H_o$rejected, H_1: there is no significant difference in μ_1 than μ_2, $\overline{\mu_1} \leq \overline{\mu_2}$
- ✓ If Sig.value ≤ .05 – $H_o$accepted, there is asignificant difference in μ_1 than μ_2, $\overline{\mu_1} > \overline{\mu_2}$.

From table 4.3 there was a significant average difference in

- ✓ FGGD than FRD – [t(10) = 147.72, p<0.05], [t(10) =128.11, p<0.05]
- ✓ FGGD than FLLD –[t(10) =673.97, p<0.05], [t(10) =1201.15, p<0.05]
- ✓ FGGD than FGRD– [t(10) =362.45, p<0.05], [t(10) =6354.15, p<0.05] for lower, upper α-cuts respectively

5. Conclusion:

Here we successfully established the fuzzy models to calculated the effect of oxytocin by estimate the mean and variance of FGGD, FLLD, FRD, FGRD. The mean values are increased for lower alpha cuts and decreased for upper alpha cuts. The testing of hypothesis shows that there is a significant difference in FGGD than FLLD, FGRD, FRD. FGGD fits well for measuring the effect of oxytocin in PPH.

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