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Bayesian Model Analyses of Media Impact

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ABSTRACT

This research has used the Bayesian Method to assess the impact of crime news in television media accurately. Based on Bayesian theory, the served samples of 350 calculated the posterior probability of every indicator, and then, the research of Bayesian SEM (Structural Equation Model) calculated the posterior probability of the multi-indicator comprehensive of crime news and its impact on television assessment. Next, we used the Bayesian graph to assess the Regression weights, Means, Covariances and Variances of every sub system of the posterior probability of the Bayesian formula.

Keywords: *Bayesian, SEM, Reach, awareness, probability indicator. Crime News, and Media.*

INTRODUCTION

Nowadays with the increased research being taking place in such events, the Bayesian method has received greater attention. It uses objective probability estimations to estimate the probability of some unknown states [1-3]. This method can also describe uncertain information and conduct uncertainty reasoning. When compared with other existing assessment methodology, the Bayesian method's superiority lies in giving the probability or tendency towards a certain grade to which the system belongs and not just simply giving the grade [4-6]. The greatest advantage that the Bayesian method has is that of a simple principle and calculation process from which reliable results can be obtained even for small samples. This is the reason why it is widely being used and here it has been used to study the impact of crime news quality assessment. Fault diagnosis and risk assessment are rarely been used for assessment [7-9].

The objective of this research is to assess the impact of crime news accurately using the Bayesian Method. The proposed method will address uncertain information and assessment results and can help in identifying the specific crime-related problems in Chennai city. Hence appropriate measures were taken for effective crime awareness assessment [10].

Bayesian inference is a technique of statistical inference wherein Bayes' theorem is used to exchange the probability for a hypothesis as higher evidence or information will turn out to be available [11-13]. Bayesian inference is an primary approach in knowledge, and in particular in mathematical expertise. Bayesian updating is in exact most important inside the dynamic analysis of a sequence of facts. Bayesian inference has determined program in a huge variety of exercises, along with technology, engineering, philosophy, medication, sport, and legislation.

In the philosophy of option precept, Bayesian inference is carefully related to subjective possibility, commonly referred to as "Bayesian possibility".

SUMMARY OF POSTERIOR DISTRIBUTION

Mean

The mean or average is an important measure of central tendency for any distribution. It is commonly known as arithmetic mean, which often is referred along with terms like standard deviation that describes the central location of the data whereas the standard deviation describes the spread.

The term in Geometry or Statistics mean can be derived from the formula:

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \quad \ldots\ldots\ldots\ldots\ldots \quad (1)$$

The above illustration helps in finding out the mean value in probability statistics. The estimated posterior means which are calculated as:

$$X = \frac{1}{N-B}(X_{B+1}, X_{B+2} + \cdots + X_N)$$

Where N is the number of observations, B is the number of burn-in observations and $X$is the value of a single estimated he i-th the observation.

Standard Error (S.E)

An estimate, SE, of the standard error of obtained by the method of batch means. SE is a measure of the variability that is attributable to the fact that N is finite.

$$S = \sqrt{\frac{\sum_{i-1}^{n}(x_i - \bar{x})^2}{n-1}} \ldots\ldots\ldots\ldots\ldots \quad (2)$$

Where SE is standard error, x is measurement; X is arithmetic mean of n measurements.

O estimate population standard deviation, σ (sigma).

Estimating the standard deviation of the population is not important in this study but since substituting the sample standard deviation (s) for σ (sigma) while standardizing the sample mean, it is worth to point out that s is an unbiased estimator for σ (sigma).

If we divide by n instead of n – 1 for population standard deviation, then sample variance would be of slight underestimation. Therefore dividing by n – 1 is going to fulfill an unbiased goal of point estimator.

The reason that the formula for s, introduced in the Exploratory Data Analysis unit, involves division by n – 1 instead of by n is the fact that it is unbiased estimator in practice.

S.D. Standard Deviation

The estimated standard, deviation of the posterior distribution has calculated as.

$$\sigma = \sqrt{\frac{1}{N}\sum_{i-1}^{N}(x_i - \bar{x})^2} \quad \ldots\ldots\ldots\ldots\ldots(3)$$

σ = standard deviation, xi = each value of dataset, x (with a bar over it) = the arithmetic mean of the data (This symbol will be indicated as mean from now), N = the total number of data points, ∑ (xi - mean) ^2 = the sum of (xi - mean) ^2 for all data points

C.S. Convergence Statistic

The Convergence Statistic is computed as

$$CS = \frac{\sqrt{SD^2 + SE^2}}{\sqrt{SD^2}} = \sqrt{1 + \frac{SE^2}{SD^2}} \quad \ldots\ldots\ldots\ldots\ldots (4)$$

Regression

The Linear Regression option calculates the p-value under the assumption that there are no empty values in the data table. Let n be the total number of values and denote by (xi, yi), i = 1, n the set of data points to fit a straight line;

$$y = \beta_0 + \beta_1 x$$

The last square estimate of β_0 *and* β_1 are:

$$\beta_0 = (\frac{\sum_{i=1}^{n} x_i^2)(\sum_{i=1}^{n} y_i) - (\sum_{i=1}^{n} x_i)(\sum_{i=1}^{n} x_i y_i)}{n\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2}$$

$$\beta_1 = (\frac{\sum_{i=1}^{n} x_i y_i - (\sum_{i=1}^{n} x_i) - (\sum_{i=1}^{n} y_i)}{n\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2} \quad \ldots\ldots\ldots \quad (5)$$

The p-value is then calculated from the F-distribution where the F-statistic is calculated with the sum of squares between the estimated line and the total mean of the yi's having one degree of freedom as numerator and the residual sum of squares divided by the number of degrees of freedom (n-2) as denominator.

Variance

The variance can be obtained using either of the following formulas:

$$s^2 = \sum_{i=1}^{N}(x_i - \bar{x})^2/(N-1)$$

$$s^2 = \sum_{i=1}^{N} x^2{}_i - (\sum_{i=1}^{N} x_i)^2/(N1)/(N-1) \quad (6)$$

Since the formulas are algebraically equal, the one preferred is often the one easier to use (or remember). Care must be taken to choose an algorithm that produces accurate results under a wide variety of conditions without requiring extensive computer time. Often, these two considerations must be balanced against each other.

Covariances

Since the variances of the two measurement periods are nearly equal, a covariance structure that assumes the variances are equal may work as well as the unstructured covariance.

By assuming the variances to be equal, the model would use one less covariance parameter, and in general you want to use the simplest model that fits the data well.

$$Cov(X,Y) = \frac{\sum_{i=1}^{n} x_i y_i - (\sum_{i=1}^{n} xi)(\sum_{i=1}^{n} y_i)/n}{n} \quad (7)$$

Bayesian analysis is a statistical technique, which endeavors to estimate parameters of an underlying distribution centered at the decided distribution. Start with a "earlier distribution" which will also be centered totally on something, along with an evaluation of the relative likelihoods of parameters or the results of non-Bayesian observations. In practice, it is usual to rely on a uniform distribution over the proper kind of values for the prior distribution.

Methodology

Conceptual Model Diagram for crime news and its impact figure; 1 (SEM) has been assessed using Bayesian Theory. Based on Bayesian theory, the surveyed samples of 350 calculated the posterior probability of every indicator, and then, calculated the posterior probability of the multi-indicator comprehensive of crime news and its impact on television assessment. For the multi-layered crime news, assessment can be seen as an indicator and then, we recalculated the posterior. Next, we used the SEM method to calculate the weights of every subsystem of theposterior probability of the Bayesian method are as follows.

Result

Regression Weights

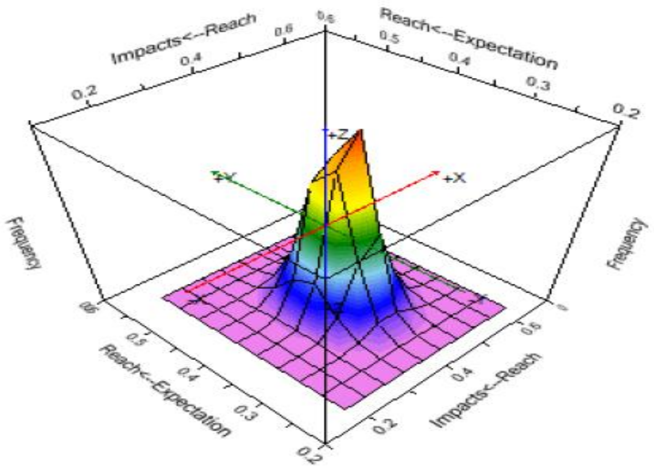

Figure1. *Regression weights*

Table1. *Posterior Distribution of a Parameter*

	Mean	S.E.	S.D.	C.S.	Median	50% Lower bound	50% Upper bound
Impacts<--Reach	0.412	0.001	0.047	1.000	0.411	0.380	0.444
Reach<-- xpectation	0.382	0.001	0.038	1.000	0.382	0.356	0.408

Above is a graph Figure: 1 shows the posterior distribution of the regression weight for using Reach to predict Impact and Expectations to predict Reach. The graph shows everything that is known about the value of the regression weight.

There is about a 50-50 chance that the regression weight is between -0.444 <- 0.380 and. 0.408 <- 0.356. The regression weight is almost guaranteed value to be 0.382 and 0.412 (Table: 1).

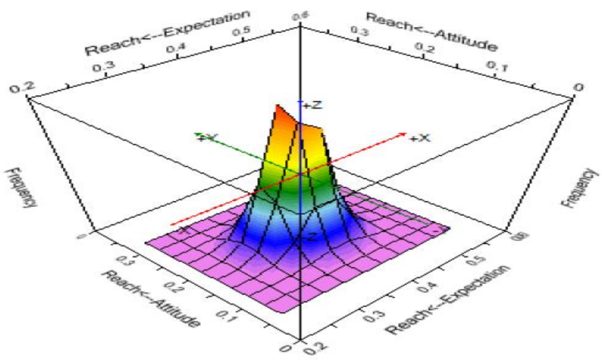

Figure2. *Regression weights*

Table2. *Posterior Distribution of a Parameter*

	Mean	S.E.	S.D.	C.S.	Median	50% Lower bound	50% Upper bound
Reach<--Expectation	0.382	0.001	0.038	1.000	0.382	0.356	0.408
Reach<--Attitude	0.190	0.001	0.031	1.000	0.190	0.169	0.211

Above is a graph (Figure: 2 & Table: 2) shows the posterior distribution of the regression weight for using Expectation to predict Reach and Attitude to predict Reach. The graph shows everything that is known about the value of the regression weight. There is about a 50-50 chance that the regression weight is between 0.408 <-0.356 and. 0.211<-0.169. The regression weight is almost guaranteed value to be 0.190 and 0.382.

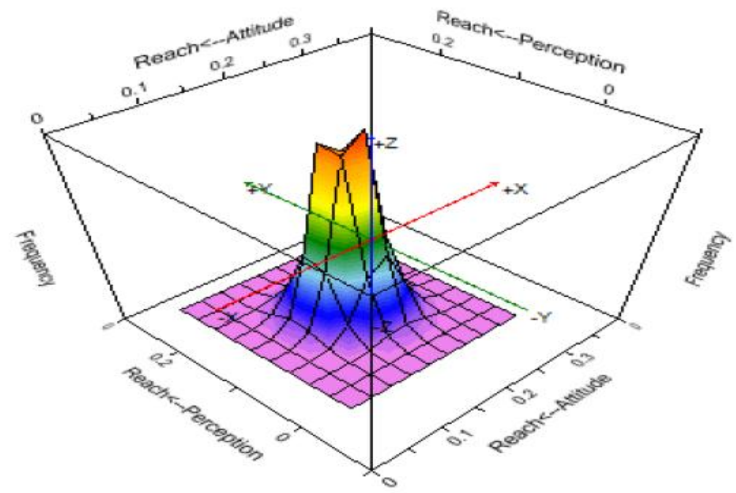

Figure3. *Regression weight*

Table3. *Posterior Distribution of a Parameter*

	Mean	S.E.	S.D.	C.S.	Median	50% Lower bound	50% Upper bound
Reach<--Attitude	0.190	0.001	0.031	1.000	0.190	0.169	0.211
Reach<--Perception	0.126	0.001	0.031	1.000	0.126	0.105	0.147

Above is a graph (Figure: 3 & Table: 3) shows the posterior distribution of the regression weight for using Attitude to predict Reach and Perception to predict Reach. The graph shows everything that is known about the value of the regression weight. There is about a 50-50 chance that the regression weight is between 0.211 <-0.169 and. 0.147<-0.105. The regression weight is almost guaranteed value to be 0.126 and 0.190.

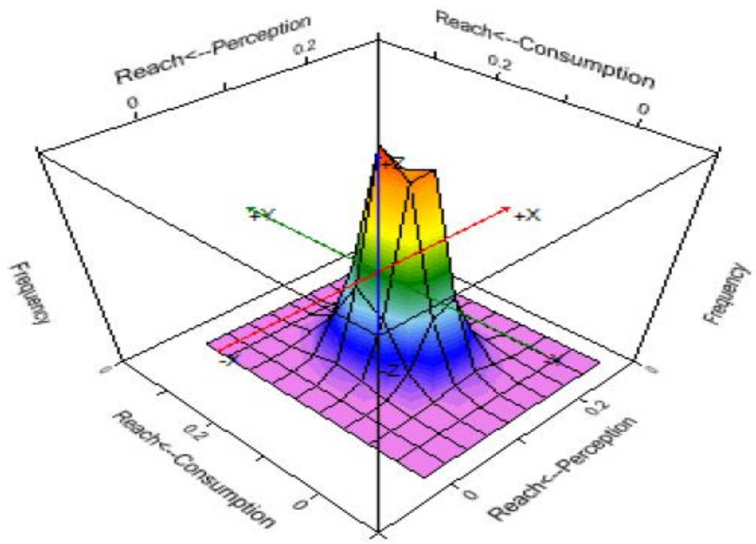

Figure4. *Regression weights*

Table4. *Posterior Distribution of a Parameter*

	Mean	S.E.	S.D.	C.S.	Median	50% Lower bound	50% Upper bound
Reach<--Perception	0.126	0.001	0.031	1.000	0.126	0.105	0.147
Reach<--Consumption	0.143	0.001	0.048	1.000	0.143	0.111	0.176

Above is a graph (Figure: 4 & Table: 4) shows the posterior distribution of the regression weight for using Perception to predict Reach and consumption to predict Reach. The graph shows everything that is known about the value of the regression weight. There is about a 50-50 chance that the regression weight is between - 0.147 <- 0.105 and. 0.176<- 0.111. The regression weight is almost guaranteed value to be 0.143 and 0.126.

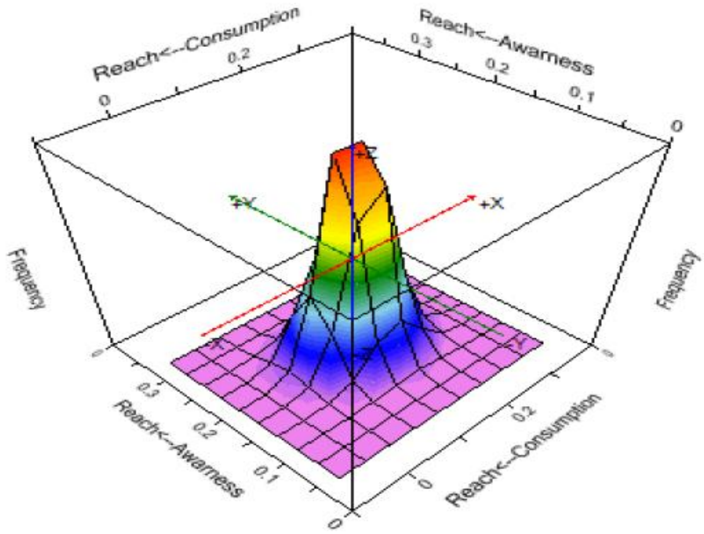

Figure5. *Regression weights*

Table5. *Posterior Distribution of a Parameter*

	Mean	S.E.	S.D.	C.S.	Median	50% Lower bound	50% Upper bound
Reach<--Consumption	0.143	0.001	0.048	1.000	0.143	0.111	0.176
Reach<--Awareness	0.190	0.001	0.030	1.000	0.190	0.170	0.210

Above is a graph (Figure: 5 & Table: 5) shows the posterior distribution of the regression weight for using Consumption to predict Reach and Reach to predict Awareness. The graph shows everything that is known about the value of the regression weight. There is about a 50-50 chance that the regression weight is between 0.176 <-0.111 and. 0.210 <-0.170. The regression weight is almost guaranteed value to be 0.190 and 0.143.

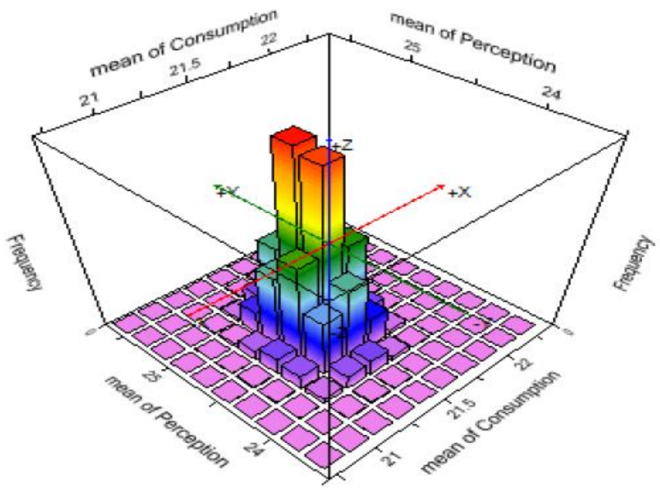

Figure6. *Mean*

Table6. *Posterior Distribution of a Parameter*

	Mean	S.E.	S.D.	C.S.	Median	50% Lower bound	50% Upper bound
Consumption	21.472	0.003	0.153	1.000	21.471	21.369	21.573
Perception	24.639	0.006	0.239	1.000	24.639	24.478	24.803

Above is a graph (Figure: 6 & Table: 6) shows the posterior distribution of the Mean for using Consumption to predict Perception. The graph shows everything that is known about the value of the Mean. There is about a 50-50 chance that the Mean weight is between 21.573 <-21.369 and. 24.803<-24.478. The Mean is almost guaranteed value to be 24.639 and 21.472.

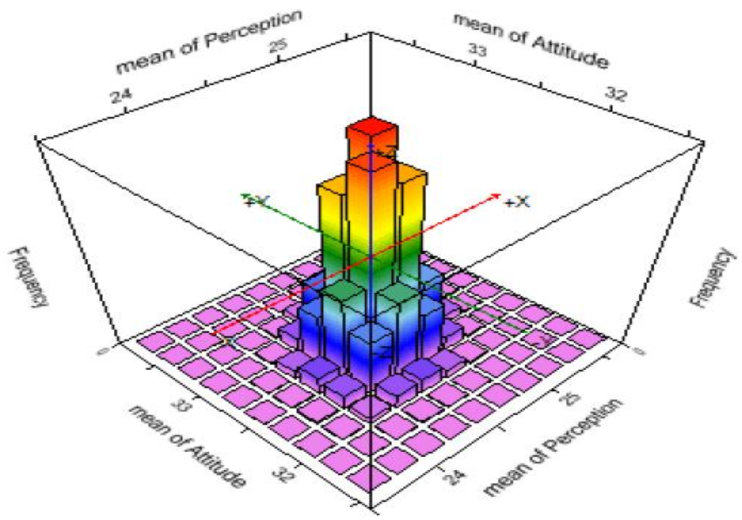

Figure7. *Mean*

Table7. *Posterior Distribution of a Parameter*

	Mean	S.E.	S.D.	C.S.	Median	50% Lower bound	50% Upper bound
Perception	24.639	0.006	0.239	1.000	24.639	24.478	24.803
Attitude	32.681	0.006	0.260	1.000	32.681	32.505	32.856

Above is a graph (Figure: 7 & Table: 7) shows the posterior distribution of the mean value for using Perception to predict Attitude. The graph shows everything that is known about the value of the mean. here is about a 50-50 chance that the mean is between 24.803 to 24.478, 32.856 to 32.505. The mean is almost guaranteed value to be 32.681and 23.639.

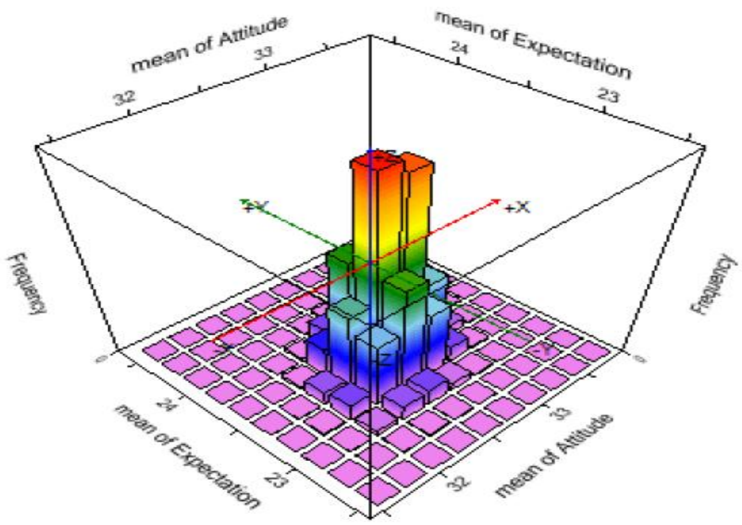

Figure8. *Mean*

Table8. *Posterior Distribution of a Parameter*

	Mean	S.E.	S.D.	C.S.	Median	50% Lower bound	50% Upper bound
Attitude	32.681	0.006	0.260	1.000	32.681	32.505	32.856
Expectation	23.463	0.005	0.209	1.000	23.459	23.321	23.601

Above is a graph (Figure:8 & Table: 8) shows the posterior distribution of the mean value for using Attitude to predict Expectation. The graph shows everything that is known about the value of the mean. There is about a 50-50 chance that the mean is between 32.856 to 32.505, 23.601 to 23.321.The mean is almost guaranteed value to be 23.463and 32.681.

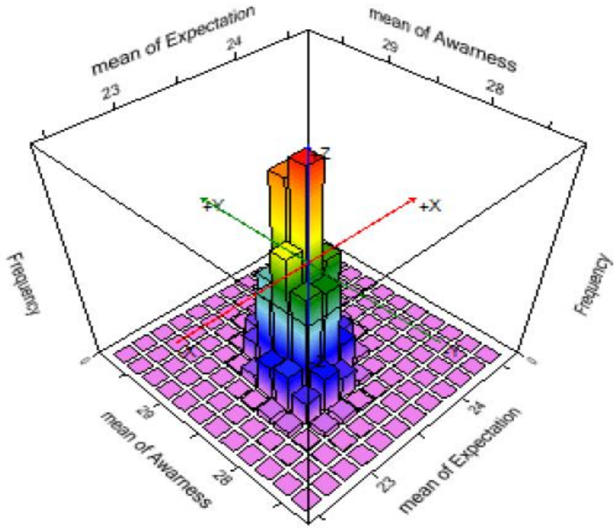

Figure9. *Mean*

Table9. *Posterior Distribution of a Parameter*

	Mean	S.E.	S.D.	C.S.	Median	50% Lower bound	50% Upper bound
Expectation	23.463	0.005	0.209	1.000	23.459	23.321	23.601
Awarness	28.540	0.007	0.276	1.000	28.539	28.354	28.724

Above is a graph (Figure: 9 & Table: 9) shows the posterior distribution of the mean value for using Expectation to predict Awareness. The graph shows everything that is known about the value of the mean. There is about a 50-50 chance that the mean is between 23.601to 23.321, 28.724to 28.354. The mean is almost guaranteed value to be 28.540and 23.463.

Intercepts

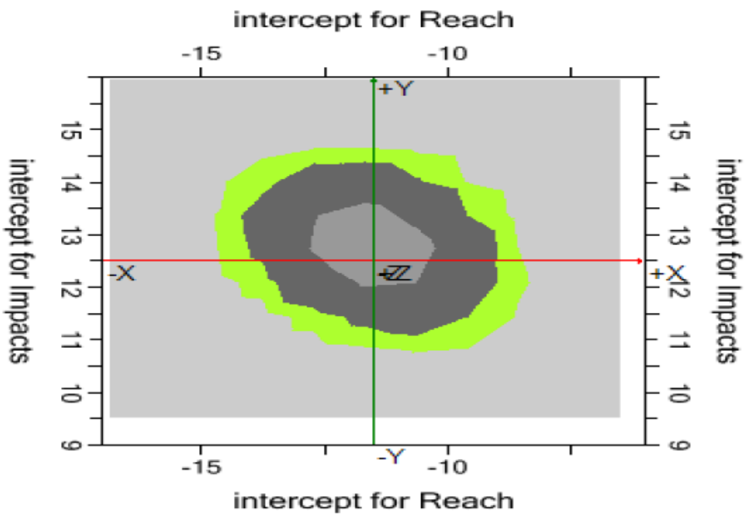

Figure10. *Intercepts*

Table10. *Posterior Distribution of a Parameter*

	Mean	S.E.	S.D.	C.S.	Median	50% Lower bound	50% Upper bound
Reach	-11.474	0.031	1.186	1.000	-11.473	-12.282	-10.674
Impacts	12.792	0.014	0.739	1.000	12.803	12.301	13.286

Above is a graph (Figure: 10 & Table: 10) shows the posterior distribution of the Intercepts value for using Reach to predict Impacts. The graph shows everything that is known about the value of the Intercepts. There is about a 50-50 chance that the Intercepts is between -10.674 to --12.282 and 13.286 to 12.301The Intercepts is almost guaranteed value to be -11.53and 12.792.

Convergence

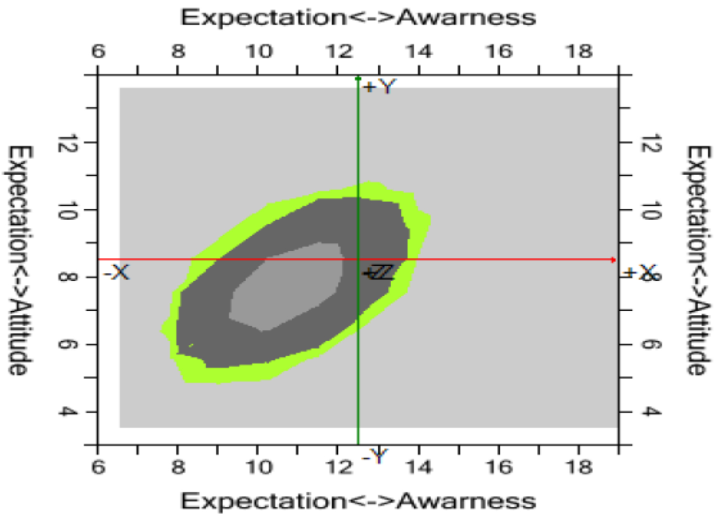

Figure11. *Covariances*

Table11. *Posterior Distribution of a Parameter*

	Mean	S.E.	S.D.	C.S.	Median	50% Lower bound	50% Upper bound
Expectation<>Awareness	10.838	0.030	1.229	1.000	10.785	9.978	11.643
Expectation<->Attitude	7.793	0.027	1.103	1.000	7.747	7.037	8.509

Above is a graph (Figure: 11 & Table: 11) shows the posterior distribution of the Covariances for using Awareness to predict Expectation and Expectation to predict Attitude. The graph shows everything that is known about the value of the Covariances. There is about a 50-50 chance that the Covariances is between 11.643 <-> 9.978 and 8.509 <->7.037. The Covariances is almost guaranteed value to be 10.838 and 7.793...

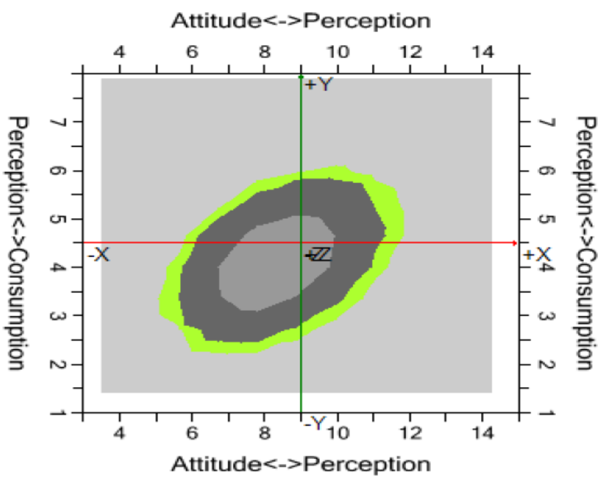

Figure12. *Covariances*

Table12. *Posterior Distribution of a Parameter*

	Mean	S.E.	S.D.	C.S.	Median	50% Lower bound	50% Upper bound
Attitude<->Perception	8.396	0.033	1.270	1.000	8.358	7.519	9.214
Perception<>Consumption	4.173	0.016	0.744	1.000	4.145	3.662	4.651

Above is a graph (Figure: 12 & Table: 12) shows the posterior distribution of the Covariances for using Attitude to predict Perception and Perception to predict Consumption. The graph shows everything that is known about the value of the Covariances. There is about a 50-50 chance that the Covariances is between 9.214<-> 7.519 and 4.651<->3.662. The Covariances is almost guaranteed value to be 3.662 and 4.173.

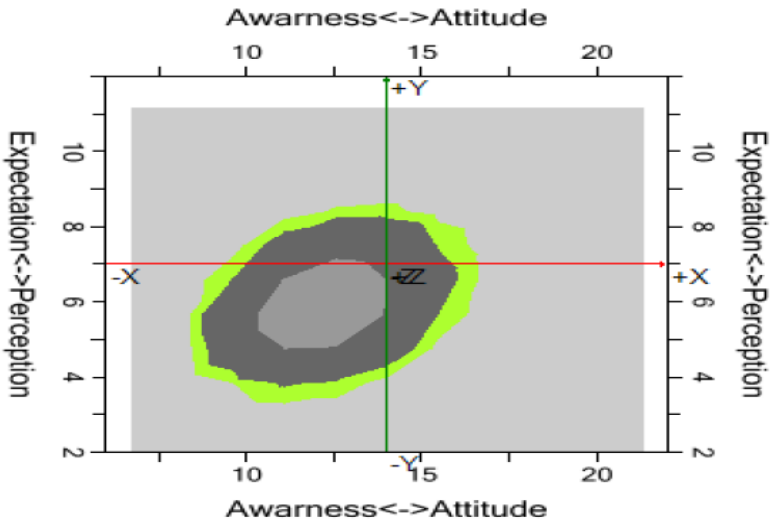

Figure13. *Covariances*

Table13. *Posterior Distribution of a Parameter*

	Mean	S.E.	S.D.	C.S.	Median	50% Lower bound	50% Upper bound
Awareness<->Attitude	12.410	0.044	1.520	1.000	12.352	11.364	13.401
Expectation<>Perception	5.970	0.024	0.993	1.000	5.932	5.298	6.613

Above is a graph (Figure: 13 & Table: 13) shows the posterior distribution of the Covariances for using Awareness to predict Attitude and Expectation to predict Perception. The graph shows everything that is known about the value of the Covariances. There is about a 50-50 chance that the Covariances is between 13.401<-> 11.364 and 6.613<->5.298. The Covariances is almost guaranteed value to be 12.410 and 5.970.

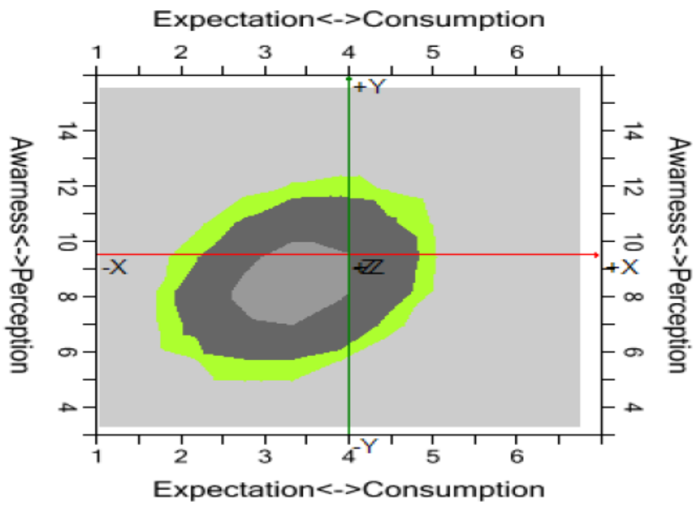

Figure14. *Covariances*

Table14. *Posterior Distribution of a Parameter*

	Mean	S.E.	S.D.	C.S.	Median	50% Lower bound	50% Upper bound
Expectation<>Consumption	3.359	0.012	0.643	1.000	3.338	2.914	3.788
Awareness<->Perception	8.615	0.030	1.350	1.000	8.590	7.689	9.482

Above is a graph (Figure: 14 & Table: 14) shows the posterior distribution of the Covariances for using Expectation to predict Consumption and Awareness to predict Perception. The graph shows everything that is known about the value of the Covariances. There is about a 50-50 chance that the Covariances is between 3.788 <-> 2.914 and 9.482<->7.689. The Covariances is almost guaranteed value to be 3.359 and 8.615.

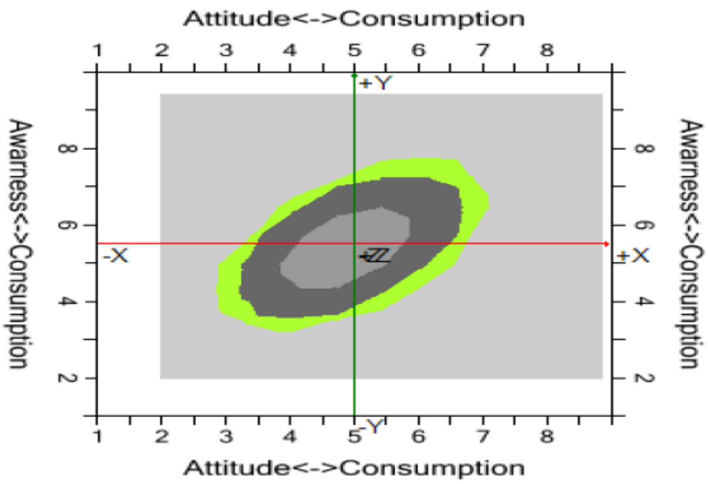

Figure15. *Covariances*

Table15. *Posterior Distribution of a Parameter*

	Mean	S.E.	S.D.	C.S.	Median	50% Lower bound	50% Upper bound
Attitude<->Consumption	4.943	0.022	0.799	1.000	4.915	4.401	5.460
Awareness<>Consumption	5.441	0.018	0.881	1.000	5.401	4.832	6.001

Above is a graph (Figure: 15 & Table: 15) shows the posterior distribution of the Covariances for using Attitude to predict Consumption and Awareness to predict Consumption. The graph shows everything that is known about the value of the Covariances. There is about a 50-50 chance that the Covariances is between 5.460 <-> 4.401 and 6.001<->4.832.The Covariances is almost guaranteed value to be 4.943 and 5.441.

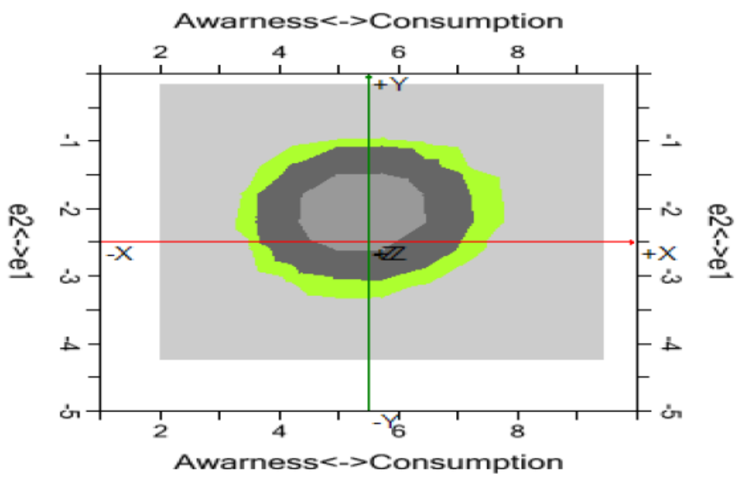

Figure16. *Covariances*

Table16. *Posterior Distribution of a Parameter*

	Mean	S.E.	S.D.	C.S.	Median	50% Lower bound	50% Upper bound
Awareness<>Consumption	5.441	0.018	0.881	1.000	5.401	4.832	6.001
e2<->e1	2.072	0.007	0.457	1.000	-2.058	-2.370	-1.760

Above is a graph (Figure: 16 & Table: 16) shows the posterior distribution of the Covariance's for using Awareness to predict Consumption and e2 to predict e1. The graph shows everything that is known about the value of the Covariance's. There is about a 50-50 chance that the Covariance's is between 6.001<-> 4.832and -1.760<->-2.370. The Covariance's is almost guaranteed value to be 5.441and 2.072.

CONCLUSION

The Bayesian was consistent with the actual situation. This finding indicated that the Bayesian method was feasible in finding out the results about the impact on TV viewers when crime news is being telecasted with a simple calculation process. The important mission of providing a platform to assess the impact of crime news in Chennai City was assessed; Impact of crime news awareness and expectation had seriously reflected the sustainable development of the regional counter mechanism to improve the utilization of crime news sources. The need of the hour is to take effective countermeasures and make good use of technology to improve the level of the crime awareness and prevention in Chennai city.

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