



Digital Revolution in Livestock Farming: Empowering Indian Farmers with TNAU Cattle Expert System and User Feedback Insights

C. Karthikeyan¹, S.R. Shri Rangasami², S. Aravindh Kumar¹,
R. Ajaykumar³, K. Harishankar⁴, M. Thirunavukkarasu⁵, R. Karthika⁵

10.18805/IJAR.B-5383

ABSTRACT

Background: Cattle husbandry in India is a cornerstone of the agricultural sector, supporting the livelihoods of millions of farmers. However, the industry grapples with challenges such as disease outbreaks, low productivity and limited access to veterinary services. The TNAU Cattle Expert System Application represents a digital innovation aimed at addressing these challenges by providing farmers with real-time guidance on various aspects of cattle management.

Methods: The study was meticulously conducted in Tamil Nadu over the years of both 2022 and 2023. Feedback was systematically collected from 523 users of the TNAU Cattle Expert System Application. Text analysis tools were employed to categorize sentiments as positive, negative or neutral using Azure machine learning software in MS Excel. Log Regression was carried out to identify the variance of feedback sentiments followed by cluster analysis through jamovi further classified feedback into distinct groups, revealing patterns in user engagement.

Result: Positive feedback praised the application's detailed information on cattle protection and disease precautions, particularly for FMD, BRD, Mastitis, Johne's disease, Brucellosis, Clostridia diseases and BVD. "Delicate" users (38.54%) gave appreciative feedback, "Arbitrator" users (26.04%) offered diverse opinions, "Eloquent" users (18.75%) expressed positive sentiments, while "Criticizer" (12.50%) and "Harsh stringer" users (4.17%) provided critical insights.

Key words: Animal diseases diagnosis, Cattle expert system, Cattle husbandry, Feedback-cluster analysis, Log-linear regression, M-agricultural applications.

INTRODUCTION

Cattle play a crucial role in the global agricultural industry, serving as a primary source of protein and dairy products for human consumption (Tsusaka *et al.*, 2016). Cattle husbandry, also known as cattle farming or ranching, refers to the agricultural practice of raising and breeding cattle for various purposes, including meat, milk and other by-products such as leather and dung (Meena *et al.*, 2021 and Ssewanyana *et al.*, 2021). Additionally, they contribute to the economy through meat and dairy exports, as well as providing traction for agricultural activities in some regions (Ahuja and Ramachandran, 2021). Cattle husbandry encompasses various facets, including nutrition management, disease prevention and treatment, breeding and reproduction and ensuring the overall welfare of the animals (Ndambi *et al.*, 2009). It requires knowledge and skills in animal care, genetics, nutrition and veterinary medicine to ensure the health and productivity of the cattle herd.

In recent years, cattle farmers have faced numerous challenges in managing their herds effectively (Mapiye *et al.*, 2020). These challenges include fluctuating market prices for meat and dairy products, increasing input costs such as feed and veterinary services (Baral and Sah, 2020), climate change impacts on grazing lands and water availability and the emergence of new diseases and

¹Department of Agricultural Extension and Rural Sociology, Tamil Nadu Agricultural University, Coimbatore-641 003, Tamil Nadu, India.

²Department of Forage Crops, Tamil Nadu Agricultural University, Coimbatore-641 003, Tamil Nadu, India.

³Department of Agronomy, Vanavarayar Institute of Agriculture, Pollachi-642 103, Tamil Nadu, India.

⁴Department of Social Science, Vanavarayar Institute of Agriculture, Pollachi-642 103, Tamil Nadu, India.

⁵Department of Veterinary and Animal Science, Tamil Nadu Agricultural University, Coimbatore-641 003, Tamil Nadu, India.

Corresponding Author: S.R. Shri Rangasami, Department of Forage Crops, Tamil Nadu Agricultural University, Coimbatore-641 003, Tamil Nadu, India. Email: shrirangasamisr@tnau.ac.in

How to cite this article: Karthikeyan, C., Rangasami, S.R.S., Kumar, S.A., Ajaykumar, R., Harishankar, K., Thirunavukkarasu, M. and Karthika, R. (2024). Digital Revolution in Livestock Farming: Empowering Indian Farmers with TNAU Cattle Expert System and User Feedback Insights. Indian Journal of Animal Research. 58(9): 1622-1629. doi: 10.18805/IJAR.B-5383.

Submitted: 16-04-2024 **Accepted:** 26-06-2024 **Online:** 18-07-2024

pests affecting cattle health (Ajaykumar *et al.*, 2024). Moreover, rapid urbanization and land use changes have led to the fragmentation of grazing lands and encroachment on traditional cattle farming areas, posing additional

challenges to cattle farmers. Additionally, limited access to timely and accurate information on best practices in cattle husbandry, disease prevention and treatment further complicates the management of cattle herds (Yilma *et al.*, 2020).

In this context, the current scenario of cattle husbandry emphasizes the need for innovative solutions to address these challenges and enhance the sustainability and profitability of cattle farming practices. Given the complexities and challenges faced by cattle farmers, there is a growing demand for quick information supply and efficient diagnosis methods to support decision-making in cattle husbandry. Expert systems, powered by artificial intelligence and machine learning technologies (Karthikeyan, 2018), offer promising solutions to address these needs (Yousif *et al.*, 2017). By integrating vast databases of knowledge on cattle management, disease diagnostics and treatment protocols, expert systems can provide real-time guidance and recommendations to cattle farmers. These systems leverage advanced algorithms to analyze data from various sources, including field observations, laboratory tests and historical records, to generate personalized insights and actionable recommendations for farmers. By enabling rapid access to expert knowledge and decision support tools (Ikram and Afzal, 2019 and Kumar and Karthikeyan, 2019), expert systems can empower cattle farmers to make informed decisions, optimize resource allocation and mitigate risks associated with disease outbreaks and environmental challenges.

TNAU Cattle Expert System is a mobile application available in Bilingual mode in google play store (https://play.google.com/store/apps/details?id=com.cdac.tnau_cattle_eng&hl=en_IN&gl=US) the need for creating the TNAU Cattle Expert System Application arises from the complex challenges faced by cattle farmers in modern agricultural practices. Cattle husbandry involves a multitude of tasks ranging from nutrition management to disease prevention, breeding and general welfare maintenance. However, navigating these challenges effectively requires access to accurate information, expert guidance and innovative tools. Traditional methods of disseminating information and providing support to cattle farmers may be limited by factors such as geographical constraints, language barriers and the availability of qualified veterinary professionals. In this context, the development of user-friendly mobile application like the TNAU Cattle Expert System becomes crucial (Karthikeyan, 2018).

Creating an application is the toughest part but analysing the application user's feedback (Singh and Paul, 2021) is much vital. The essential need to measure the feedback of TNAU Cattle Expert System (TNCEs) Application users to ensure its effectiveness and relevance in addressing the needs of cattle farmers. By systematically gathering feedback from users (Hattie and Zierer, 2019), it could be processed and analysed to gain valuable insights into user experiences, preferences and areas for

improvement. This feedback can help identify usability issues, content gaps and feature requests, allowing for iterative enhancements to the application over time. Moreover, measuring user feedback enables continuous evaluation of the application's impact on cattle husbandry practices and the livelihoods of farmers. Furthermore, it has direct implications for enhancing cattle husbandry practices and addressing the challenges faced by cattle farmers. By incorporating user suggestions and addressing concerns, the application can evolve into a more robust and user-centric tool for cattle farmers (Kumar and Karthikeyan, 2019). Ultimately, by utilizing user feedback to drive continuous improvement, the TNAU Cattle Expert System Application has the potential to empower cattle farmers with valuable knowledge, tools and resources to overcome challenges, increase productivity and improve the overall sustainability of cattle farming practices.

MATERIALS AND METHODS

The study was undertaken in Tamil Nadu during the consecutive years of 2022 and 2023. The investigate involved gathering feedback systematically from users of the TNAU Cattle Expert System app, available in both English and Tamil versions through Google forms. Due to its wide availability, individuals across India could download and utilize the application, making the research scope national. The google forms were circulated to 740 TNCEs application users, out of that 523 (70.67%) users provided their feedbacks. The data cleaning phase was then undertaken to prepare for opinion mining, where text was analysed to categorize opinions as positive, negative, or neutral using Azure machine learning software. This process generated opinion scores ranging from 0 to 1, providing insights into user feedback nature.

Opinion	Opinion score
Positive	Closes to 1
Neutral	Circles around 0.5
Negative	Closes to 0

In opinion analysis (Karthikeyan and Kumar, 2022), it's crucial to account for the language preferences of mobile application users, often inclined towards expressing opinions in their native tongue. Accurately identifying the language used becomes paramount. Additionally, data pre-processing steps are essential, involving the removal of emoticons, punctuation, hashtags, URLs and other redundant terms to prepare data for machine learning. Tokenization, breaking down words into meaningful units or tokens, facilitates text processing. For reviews in Tamil expressed in English, translations were conducted without altering meaning. Common abbreviations like "pls" for "please" were expanded for accurate analysis. Opinion analysis utilized MS Excel 365 and Azure machine learning, synthesizing feedback scores and conducting cluster analysis to categorize feedbacks

into homogeneous groups. Cluster analysis (Ahmed and Muhammad, 2021) groups similar items or individuals together. It helped to identify patterns and relationships within the dataset. Techniques k-means clustering were likely employed using the Hartigan-Wong Algorithm. It is a linkage criterion for merging clusters which is based on the minimization of the sum of squared differences between the observations in the merged clusters. The formula for updating the proximity matrix is:

$$D_{(ij),k} = 1/2 [(D_{(ik)} + D_{(jk)} + D_{(ij)})]$$

Here:

$D_{(ij),k}$ = New dissimilarity between the new cluster formed by merging clusters i and j and cluster k .

$D_{(ik)}$, $D_{(jk)}$ and $D_{(ij)}$ = Dissimilarities between clusters i and k , j and k and i and j , respectively.

The Hartigan-Wong Algorithm continues until all data points are part of a single cluster. The resulting hierarchy can be visualized using a dendrogram. Common dissimilarity measures (Euclidean distance) were employed for this analysis. Moreover, a curve distribution was computed to classify users of the TNCES mobile application according to the opinions conveyed in their feedback. Mathematical tools were employed to fit the data into a normal distribution curve, enhancing comprehension of opinion distribution among users.

Category	Criteria
$FS_1 =$	Mean - two standard deviation
$FS_2 =$	Mean - standard deviation
$FS_3 =$	Mean
$FS_4 =$	Mean + standard deviation

RESULTS AND DISCUSSION

The descriptive statistics presented in the Table 1 offer a comprehensive overview of sentiment analysis results derived from user feedback for the TNAU Cattle Expert System Application (TNCESA). The feedback was categorized into three distinct groups: Group A (Negative), Group B (Neutral) and Group C (Positive), utilizing sentiment analysis conducted through Azure Machine Learning.

Group A, comprising 88 instances of negative feedback, yields a mean sentiment score of 0.380, indicative of a

moderately negative sentiment inclination. Skewness and kurtosis analyses reveal a slight positive skewness (0.105) and negative kurtosis (-1.36), respectively, suggesting a deviation from a typical Gaussian distribution within this group. Conversely, Group B, encompassing 63 instances of neutral feedback, demonstrates a mean sentiment score of 0.506, reflective of a consistently neutral sentiment stance. The skewness indicates a strong negative inclination (-1.29) and the kurtosis suggests a distribution leaning towards lower sentiment scores (0.652), hinting at potential underlying negative sentiments within ostensibly neutral feedback instances. In contrast, Group C, consisting of 372 instances of positive feedback, presents a substantially higher mean sentiment score of 0.719, indicative of a prevailing positive sentiment among users.

The skewness nearing zero (-0.009) and the negative kurtosis (-0.525) suggest a relatively symmetrical distribution with a discernible inclination towards higher positive scores. The Shapiro-Wilk W test confirms the normal distribution of the data, as evident in Fig 1, leading to the acceptance of H_0 . These findings provide valuable insights into the sentiment distribution of user feedback for TNCESA, indicating the presence of sub-groups within these three categories and confirming the normality of the data, which facilitates further analysis.

The feedback analysis of the TNCESA application, focusing on cattle husbandry, revealed that approximately 71% of the received feedback was positive, indicating a favorable response from users. The positive feedback primarily praised the comprehensive content of the application, especially its detailed information on cattle protection and precautions against various diseases. Users expressed satisfaction with the presentation of precautions and diagnostic methods for diseases such as Foot-and-Mouth Disease (FMD), Bovine Respiratory Disease (BRD), Mastitis, Johne's disease, Brucellosis, Clostridial diseases and Bovine Viral Diarrhea (BVD), finding them highly useful for managing their cattle effectively. Furthermore, many users highlighted the application's detailed guidance on aspects ranging from feeding practices to disease diagnosis in cattle husbandry. However, amidst the positive feedback, some users raised concerns and suggestions for improvement. One notable concern was the absence of regional language support,

Table 1: Descriptive statistics of the TNCES user's feedback (n=523).

Descriptive statistics	Group A (Negative)	Group B (Neutral)	Group C (Positive)
n	88	63	372
Mean	0.380	0.506	0.719
Standard deviation	0.068	0.010	0.089
Skewness	0.105	-1.29	-0.009
Kurtosis	-1.36	0.652	-0.525
Shapiro-Wilk W	0.398 (0.117)	0.371 (0.148)	0.309 (0.112)
Minimum	0.268	0.481	0.531
Maximum	0.475	0.517	0.908

Note: H_0 is the data is normally distributed. Values inside the bracket () indicates p-value.

limiting accessibility for certain users. Additionally, criticisms were voiced regarding the quality of videos demonstrating diagnostic procedures for specific cattle diseases. Some users expressed a desire for the application to evolve into a social media platform, facilitating networking among cattle farmers and enabling marketing opportunities. Furthermore, requests were made for expanded content coverage, including information on physical injuries like fractures and broken bones, as well as details on nearby veterinary clinics and ethnolectal treatments.

The subsequent log-linear regression analysis delves deeper into the relationships between the identified sentiment groups and their impact on the overall sentiment distribution (Table 2). The model fit measures, including the coefficient of determination ($R^2 = 0.858$), adjusted R^2 (0.737) and F-statistic (728), indicate that the regression model adequately explains a substantial portion of the variance in the sentiment distribution which is statistically significant at 1 per cent level. Additionally, the Durbin-Watson statistic (DW Stat) provides insights into the presence of autocorrelation in the residuals, with a value close to 2 suggesting no significant autocorrelation.

Table 3 outlines the estimates for each predictor variable in the log-linear regression model. The intercept,

valued at 0.380, represents the baseline sentiment level when no specific sentiment category dominates, with a small standard error (SE) of 0.009 indicating the precision of this estimate. The coefficients for Group (2-1) and Group (3-1) quantify the change in sentiment scores relative to the reference group (Group 1, Negative). Specifically, a coefficient of 0.126 for Group (2-1) suggests an average increase of 0.126 units in sentiment when transitioning from Negative to Neutral sentiment, while the coefficient of 0.339 for Group (3-1) indicates a larger increase of 0.339 units when moving from Negative to Positive sentiment. These coefficients, along with their standard errors and confidence intervals, provide insights into the significance and precision of the estimated effects.

In the Table 4, the significant F-statistic of 728 ($p < .001$) indicates that the regression model as a whole is statistically significant in explaining the variance in overall sentiment scores. The sum of squares for the Group predictor variables confirms their collective significance in explaining variance, with a notable effect size ($\eta^2 = 0.737$), suggesting that approximately 73.7% of the variance in sentiment scores is accounted for by the sentiment categories.

Levene's and Bartlett's tests show significant p-values (< 0.001), indicating variance heterogeneity and sub-groups within the sentiment data, offering insights for further analysis (Table 5). The cluster analysis depicted in Fig 2

Table 2: Log-linear regression-model fit measures.

R	R^2	Adjusted R^2	F	Df1	Df2	p	DW stat	Cook's distance mean
0.858	0.737	0.736	728	2	520	<.001	1.97	0.0013

Table 3: Log-linear regression-model coefficients.

Predictor	Estimate	SE	Lower CI	Upper CI	t	p
Intercept	0.380	0.009	0.363	0.397	44.35	<.001
Group (2-1)	0.126	0.013	0.100	0.152	9.53	<.001
Group (3-1)	0.339	0.010	0.321	0.358	35.62	<.001

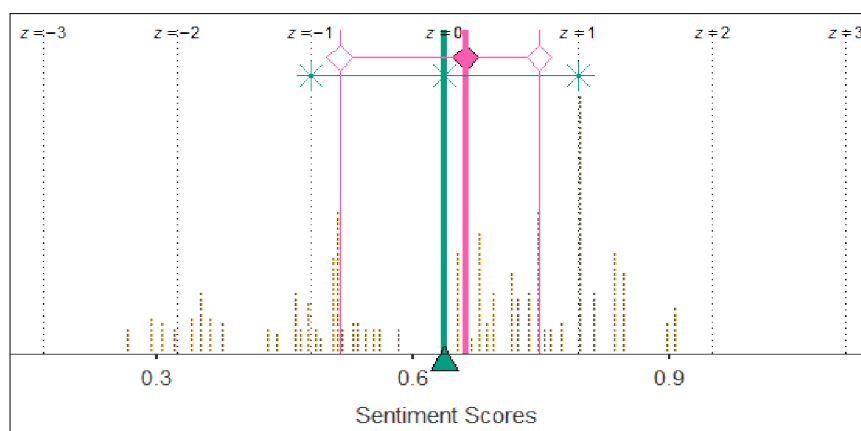


Fig 1: Dotted plot distribution of the sentiment scores of the TNCES feedback.

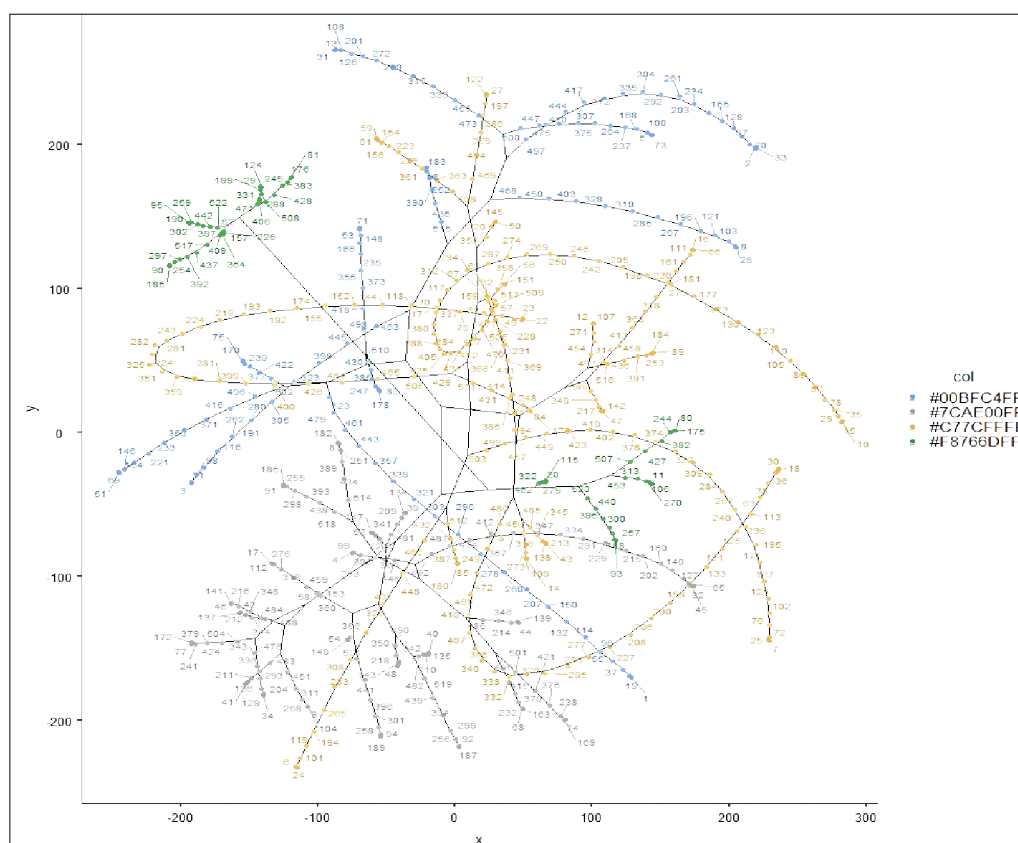


Fig 2: Cluster dendrogram representing the categorization of the TNCEs user's feedback in to various clusters.

Table 4: ANOVA-Table.

	Sum of squares	df	Mean square	F	p	η^2	η^2p	ω^2
Overall model	9.41	2	4.70659	728	< .001			
Group	9.41	2	4.70659	728	< .001	0.737	0.737	0.736
Residuals	3.36	520	0.00646					

Table 5: Homogeneity of variance tests.

	Statistic	df	df2	p
Levene's	63.7	2	520	<.001
Bartlett's	207	2		<.001

reveals discernible patterns within the user feedback dataset for the TNCEs application, effectively categorizing users into four distinct clusters denoted as C1, C2, C3 and C4. Each cluster demonstrates varying levels of agreement and engagement with the TNCEs application, reflecting the varied feedback from users.

Cluster 1 (C1), comprising 122 feedbacks, is characterized by a high level of agreement and positive sentiment towards the TNCEs application. The feedback pooled within this cluster is indicative of strong satisfaction and endorsement of the application's utility. Therefore, C1 is aptly named "Functionality Feedback," denoted in blue colour in the Fig 2, emphasizing the prevalence of more positive feedback regarding the TNCEs mobile application

usage. Cluster 2 (C2), encompassing 1115 feedbacks, exhibits a suggestive nature, reflecting users' inclination towards providing recommendations or suggestions for improvement. As such, C2 is designated as "Advisory Feedback," represented in grey colour, highlighting the constructive feedback and potential areas for enhancement identified. Cluster 3 (C3), consisting of 151 feedbacks, encompasses a blend of appreciation and criticism towards the development of the TNCEs application.

The feedback within this cluster reflects a nuanced spectrum of sentiments, including both commendations and reservations. Hence, C3 is labelled "Evaluating Feedback," underscoring the diversity of opinions and perspectives expressed in this cluster denoted as orange colour in the Fig 2. Finally, Cluster 4 (C4), comprising 135 feedbacks, is distinguished by the provision of substantial queries and inquiries, indicating a proactive engagement with the application and a desire for clarification or additional information. C4 is therefore named "Inquisitive Feedback," emphasizing the critical role of queries in elucidating and

refining the TNCES application's functionalities. The delineation of these four clusters aligns with the previous results, indicating distinct subgroups within the sentiment categories identified earlier.

In Table 1, it was mentioned that normal distribution had happened in the study, the normal distribution curve created for the study using the scores obtained also proves the same. From the normal distribution curve Fig 3, it was detected that area lying to the left of the mean opinion score of TNCES agricultural mobile application users minus two standard deviation ($\bar{x} - 2\sigma$) includes the first 4.17 per cent of the individuals to provide "Harsh stringer".

From Table 6, the next 12.50 per cent of the users were included between ($\bar{x} - \sigma$) and ($\bar{x} - 2\sigma$) were labeled as "Criticizers". At the mean opinion score of TNCES agricultural mobile application users one two standard

deviation ($\bar{x} - \sigma$), a point of inflection occurs including 26.04 per cent of the users, they were labeled as "Arbitrator". At that point, positive feedback start to increase (and level off) between the mean and other inflection point ($\bar{x} + \sigma$), where the more gentle positive feedback begins to be received are 36.84 per cent of the TNCES users labeled as "Delicate".

The last 18.75% of individuals who provided related responses (to the right of the inflection point at ($\bar{x} + \sigma$)) were labeled as "Eloquent". The normal distribution parameters can divide a continuous variable into various categories. For feedback not reaching 100%, a sixth category, "Taciturn," represents users who do not respond, aligning with the ungrouped box-whisker plot (Fig 2). Log-linear regression analysis revealed that negative feedback was close to neutral and moderately different from positive

Table 6: Categorization of TNCES mobile application users according to the normal distribution curve.

Category	Labeled name	Range	Range values	Percentage (%)
Category 1	Harsh stringer	$< FS_1$	< 0.330	4.17
Category 2	Criticizer	$FS_2 - FS_1$	0.484-0.330	12.50
Category 3	Arbitrator	$FS_3 - FS_2$	0.639-0.484	26.04
Category 4	Delicate	$FS_4 - FS_3$	0.739-0.639	38.54
Category 5	Eloquent	$> FS_4$	> 0.793	18.75

Table 7: Category distribution of TNCES mobile application users according to their nature of feedback.

Category	Utilitarian feedback (%)	Suggestive feedback (%)	Appreciative feedback (%)	Query feedback (%)	Total (%)
Harsh stringer	00.00	01.04	00.00	03.13	04.17
Criticizer	02.08	04.17	00.00	06.25	12.50
Arbitrator	05.21	06.25	07.29	07.29	26.04
Delicate	12.50	10.41	12.50	03.13	38.54
Eloquent	10.41	03.13	03.13	02.08	18.75
	30.20	25.00	22.92	21.88	100.00

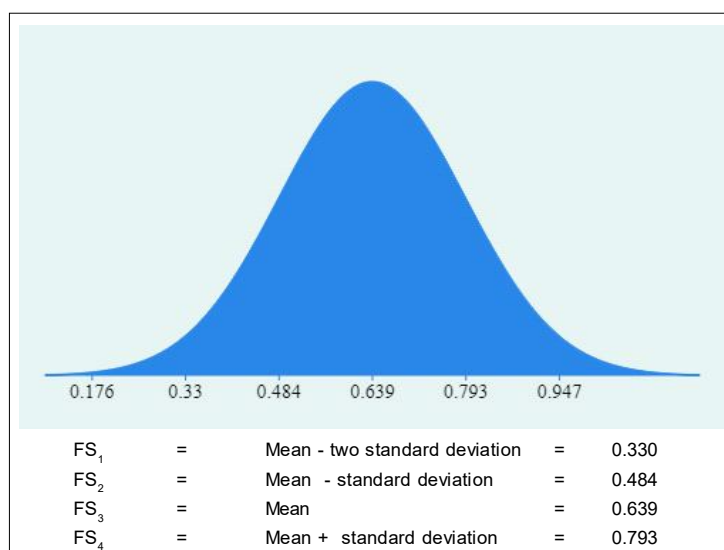


Fig 3: Normal distribution curve of the ungrouped TNCES user's opinion score.

feedback, suggesting mildly negative sentiments. Some users noted the app's lack of coverage on specific regional diseases, while others desired more detailed information on advanced topics. Positive feedback highlighted the app's effort and potential as a useful tool for cattle farmers. This diversity in feedback underscores distinct user perspectives and expectations, confirming different user and feedback types. Thus, the log-linear regression analysis validates these differences, as shown in the feedback data analysis.

Table 7 provides a clear breakdown of the feedback received for the TNCES mobile application. About 30.20 per cent of the feedback falls into the category of utilitarian feedback. Within this utilitarian feedback group, a significant portion (12.50%) was contributed by delicate users, with another substantial segment (10.41%) provided by eloquent users. This underscores the TNCES mobile application's success in meeting users' needs and expectations during their interactions with the app.

Suggestive feedback constitutes about 25.00 per cent of the total feedback received. Among these suggestions, delicate users (10.41%) and arbitrator users (06.25%) stand out as active contributors, indicating their desire for future updates and improvements in the application. These valuable insights from users should be considered in the ongoing development of the app to enhance its functionality and user experience. A noteworthy 22.92 per cent of the feedback expressed appreciation for the TNCES mobile application, lauding it as one of the best applications available, particularly for its provision of valuable information in the regional language.

Delicate users (12.50%) and arbitrator users (07.29%) feature prominently among those expressing appreciation. This positive opinion underscores the significance of providing content in regional languages to cater to a diverse user base. Lastly, query feedback emerges as a crucial category, with substantial contributions from arbitrator users (07.29%) and criticizer users (06.25%).

Addressing these query-based feedback items is essential, as they represent users seeking clarifications or additional information. These queries should be acknowledged and responded to constructively to support ongoing app development. It's important to note that within the suggestive and constructive feedback categories, there exists a minor subset of harsh critics. While these criticisms cannot be entirely avoided, they serve as valuable input for refining the application further. The box-whisker plot for different groups showed variations that happened due to the presence of various categories of individuals who provided their feedback about the TNCES mobile application was identified. The TNCES application offers numerous benefits to cattle farmers in handling their livestock and managing cattle husbandry practices. Firstly, the application provides access to comprehensive information on various aspects of cattle protection, disease

prevention and management. This enables farmers to make informed decisions and take proactive measures to safeguard the health and well-being of their cattle. Overall, the feedback possessed TNCES application as a necessary tool plays a significant role in empowering cattle farmers knowledge to enhance their productivity, profitability and sustainability in the livestock community which was supported by the results of the feedback analysis.

CONCLUSION

Based on user feedback, the TNCES application can improve in several areas to better meet the needs of cattle farmers. Positive feedback appreciated the detailed information on cattle protection and disease precautions, finding it useful for managing their cattle. Log-linear regression validated diverse user perspectives, highlighting areas for improvement. By addressing these concerns, the TNCES application can enhance cattle husbandry practices and benefit the livestock community.

Conflict of interest

The authors have no conflict of interest to declare. All co-authors have seen and agree with the content of the manuscript. We certify that the submission is original work and is not under review at any other publication.

REFERENCES

- Ahuja, V. and Ramachandran, N. (2021). Socio-economic status of dairy farmers in Punjab, India. *International Journal of Current Microbiology and Applied Sciences*. 10(6): 2404-2408.
- Ahmed, A.A. and Muhammad, R.A. (2021). A Beginners review of jamovi statistical software for economic research. *Dutse International Journal of Social and Economic Research*. 6(1): 109-118.
- Ajaykumar, R., Harishankar, K., Rangasami, S.R.S., Saravanakumar, V., Yazhini, G., Rajanbabu, V. and Premalatha, K. (2024). Growth performance, quantitative analysis and economics of broiler chickens as influenced by herbal dietary additives as alternative growth booster. *Indian Journal of Animal Research*. 58(7): 1139-1147. doi: 10.18805/IJAR.B-5326.
- Baral, S.S. and Sah, D. (2020). Economic analysis of dairy farming in hetauda sub-metropolitan City of Nepal. *Economic Journal of Nepal*. 43(1-2): 73-82.
- Hattie, J. and Zierer, K. (2019). *Visible Learning Insights*. London: Routledge. doi: 10.4324/9781351002226.
- Ikram, M. and Afzal, M. (2019). Aspect-based citation opinion analysis using linguistic patterns for better comprehension of scientific knowledge. *Scientometrics*. pp. 73-95.
- Karthikeyan, C. (2018). Completion Report of the National Agricultural Development Programme sponsored "Invigorating Extension through ICT Tools (2016-2018)", TNAU Press, Coimbatore.
- Karthikeyan, C. and Kumar, S.A. (2022). Functioning of an android app "TNAU paddy expert system" and its user's feedback sentiment analysis. *The Indian Research Journal of Extension Education*. 22(2): 113-120.

- Kumar, S.A. and Karthikeyan, C. (2019). Status of mobile agricultural apps in the global mobile ecosystem. *International Journal of Education and Development using Information and Communication Technology*. 15(3): 63-74.
- Mapiye, C., Chikumba, N., Makombe, G. and Ncube, S. (2020). Challenges faced by smallholder cattle farmers and their implications on sustainable rural livelihoods in Matabeleland South province, Zimbabwe. *Sustainability*. 12(4): 1388.
- Meena, R.K., Singh, A.K. and Singh, K.P. (2021). Analysis of economic efficiency of dairy farming in different size groups in Uttar Pradesh, India. *The Pharma Innovation Journal*. 10(3): 105-110.
- Ndambi, O.A., Hemme, T. and Latacz-Lohmann, U. (2009). Model approach to estimating the economic impact of mastitis: A case study of smallholder dairy farms in tropical Africa. *Livestock Science*. 122(1): 158-168.
- Singh, P. and Paul, S. (2021). Deep Learning Approach for Negation Handling in Opinion Analysis. *IEEE*.
- Ssewanyana, E., Kankwatsa, P. and Nalunga, J. (2021). Economic analysis of cattle farming in Wakiso District, Uganda. *International Journal of Agricultural Economics and Extension*. 8(1): 36-44.
- Tsusaka, T.W., Velasco, M., Yamano, T. and Pandey, S. (2016). Farm-level strategies for addressing the phosphorus challenge: The case of the Chinyanja Triangle in Malawi. *Agricultural Systems*. 145: 92-102.
- Yilma, Z., Berhanu, M. and Basha, B. (2020). Economic and financial analysis of smallholder dairy farming in Dugda District, East Shoa Zone, Oromia Regional State, Ethiopia. *Asian Journal of Agricultural Extension, Economics and Sociology*. pp. 38-45.
- Yousif, A., Niu, Z., Tarus, J.K. and Ahmad, (2017). A survey on opinion analysis of scientific citations. *Artificial Intelligence Review*. 52: 1805-1838.