ISSN Print: 2394-7500
ISSN Online: 2394-5869
Impact Factor: 8.4
IJAR 2022; 8(10): 104-110
www.allresearchjournal.com
Received: 25-07-2022
Accepted: 30-08-2022

Olympica Sarma
Ph.D. Scholar, Department of Animal Genetics and Breeding, G B Pant University of Agriculture & Technology, Pantnagar, Uttarakhand, India

Corresponding Author:
Olympica Sarma
Ph.D. Scholar, Department of Animal Genetics and Breeding, G B Pant University of Agriculture & Technology, Pantnagar, Uttarakhand, India

Principal component analysis of different economic traits in livestock & poultry: A comprehensive review

Olympica Sarma

DOI: https://doi.org/10.22271/allresearch.2022.v8.i10b.10199

Abstract
Principal component analysis is a mathematical technique which condenses a large collection of variables into a smaller set that still contains the majority of data in a large set. In simple term it transform a number of possibly correlated variables into smaller number of uncorrelated variables. It has been used in various fields of science and is a main part of plant and animal breeding where it helps in selection of superior and high performing animals/ plants. In the field of Animal Genetics and Breeding principal component analysis has been used in variety of animal species (cattle, buffalo, goat, sheep, pig, poultry). The various software are present that helps in carrying out principal component analysis. As there are various scientist working on various experiments, this generates a huge amount of data which is impossible to interpret. Therefore, to ease the calculations and to save the time from analyzing this huge set of data scientist turn towards principal component analysis. This becomes most widely used and acceptable method for analysis of huge set of data.

Keywords: Data sets, principal component analysis, variance, software

Introduction
With increase in advances of research there has been a drastic increase in large amount of data sets. This had made it very difficult to interpret such a large set of data within a short period and minimum error therefore, to overcome this problem a large set of techniques have been developed which leads to fulfill this requirement. The most widely used and oldest technique is PCA [1]. PCA works by condensing a large collection of variables into a smaller set that still contains the majority of data in the large set. This further helps machine learning algorithm to analyzed large set of data more quickly and easily as there are less number of unnecessary factors present in the data. A mathematical procedure that transforms a number of possibly correlated variables into smaller number of uncorrelated variables is called PCA. PCA has numerous goals including data simplification, reduction of data, classification of data, variable selection and many more [2]. The main role of PCA technique is to extract the important information from the data and use this information to access a set of summary indices called principal components. The exploitation of genetically diverse stock for improving the performance traits is one of the approaches in the breeding program. Using PCA technique residual variance in least square sense is minimized and the variance of projection coordinates is maximized. The trait which represents maximum variance direction in data is considered as first principal component1 (PC1). The trait which shows second largest source of variation in the data is considered as second principal component 2 (PC2). These two principal component forms a plane which can be visualized graphically.

History Background
Hotelling [3] described quicker ways for calculating principal component, work on principal component analysis in the 30 years after Hotelling was mainly theoretical. Various scientist namely Girshick [4, 5], Anderson [6] and Gower [7] were able to discuss theoretical results connected to PCA. Moreover, the uses, interpretation and extension of PCA was introduced by Rao [8]. Craddock [9] and Jeffers [10] were the two scientist that published articles providing practical implementation of PCA.

The time period 1991 to 2004 was very important for the development of PCA as various techniques and advancement were there in PCA including relationship between factor analysis and PCA, principal component selection etc. In the recent years PCA has been used in various discipline and many modification and adaptation are made which made it possible to calculate and interpret various types of data. Further advancement included functional PCA, simplified PCA, symbolic data PCA & robust PCA.

Need for Principal Component Analysis

The animal breeders often deal with large number of possibly correlated variables which makes the data presumably complex to handle and interpret and such difficulty in data handling and interpretation can be quelled using PCA. This technique allows reducing the number of variables considered in an evaluation of animals, which may facilitate genetic programs. PCA is one of the most common forms of factor analysis which reduces dimensions of original data set and explains the variation of original data sets. It is a multivariate technique that analyses a data table in which observation are describe by several inter correlated quantitative dependent variables [11]. PCA is means of identifying patterns in the data by their similarity and differences and the method to compress the data information without much loss of information [12]. PCA has been applied to a set of morph structural traits in order to reduce the number of traits for characterization [13].

Steps Involved in Principal Component Analysis

There are various steps that are involved in PCA. The most basic and initial step in any PCA is standardization of data set. Once the data sets are standardized there is calculation of covariance matrix for this data set. Further Eigen values and Eigen vectors are calculated for the covariance matrix. After all the necessary calculations are done sorting of Eigen values is done with correspondence to their Eigen vectors. The matrix of Eigen vectors are made by aligning the *k* Eigenvalues. After all the necessary calculations are done, the data is transferred to original matrix [14].

Z = (Value – mean) /Standard deviation
{Cov (x,x) Cov (x,y) Cov (x,z)}
{Cov (y,x) Cov (y,y) Cov (y,z)}
{Cov (z,x) Cov (z,y) Cov (z,z)}

Covariance matrix for 3- Dimensional data

For the standardization of any data set we must calculate the mean and standard deviation for each feature. A non zero vector that changes by a scalar vector when a linear transformation is applied. This type of vector is known as Eigen vector and Eigen vectors are scaled by a factor known as Eigen value. After sorting of Eigen values with their corresponding Eigen vectors we select the Eigen vectors having maximum values. The distribution of sources data's energy among each Eigen vectors is represented by Eigen values and the Eigen vectors are based for any data set. The projections of the data points give us the principal components. The first column of the projection represents first principal component, the projection of second column represents second principal component, similarly all the principal components are identified in this particular manner [14].

Final Data set = Feature Vector^T * Standardized Original Dataset^T

Principal Component Analysis in Cattle

PCA was performed to study the reproductive and growth traits in female Canchin cattle [16]. The traits analyzed in the study included calving interval, age at first calving, age at sexual maturity and body weight. Software named Statistical 8.0 (StatSoft, Tulsa, OK, USA) was used for the analysis of PCA. Total variation of 73.37% was explained by two principal components. PC1 accounted for total variation of 45.51% and PC2 explained a variation of 24.68%. It was interpreted that PC1 was genetic index related to reproductive traits and PC2 was genetic index of body weight. This study made it possible to construct a genetic index based on PC and can help in improving performance of animals.

The body conformation in Local Hill Cattle of Himalayan state of Himachal Pradesh, India was studied to analyzed biometric traits which included body length, heart girth, paunch girth, forelimb length, hind limb length, face length, forehead width, forehead length, height at hump, hump length, hook to hook distance, pin to pin distance, tail length, horn length, horn circumference and ear length. A total variance of 65.9% was shown by five principal components with 34.7% variation being explained by PC1. Moreover, it showed significant load on body length, heart girth, paunch girth, forelimb length and hind limb length. The software SAS version 9.2 was used for all the analysis in PCA. The adequacy of the samples was measured by using KMO and it was 0.75 which was higher than standard value. PCA was successfully able to explain general body correlation of general body conformation with various biometric traits [17].

The productive and reproductive traits of Guzera beef cattle were analyzed using PCA for the identification of various traits [18]. The traits selected for this study included body weight at 210 days of age, body weight at 1 year of age, body weight at 450 days of age, weight gain from birth to weaning, from weaning to 365 days of age, 1year to yearling body weight and scrotal circumference at 365 and 415 days of age. A total of 68.22% of total variance was explained by two principal components with PC1 explaining 55.15% of variance and PC2 explaining 13.07% of variance. A two groups of traits were identified in which first group was correlated to body weight and weight gain whereas second group was related to scrotal circumference. The software SAS version 9.3 was used to perform PCA.

Principal Component Analysis in Buffalo

PCA was used in Murrah buffaloes to study linear type traits to explain body conformation [19]. Traits selected for study included top wedge angle, rump slope, rump width, hip bone distance, navel flap length, brisket distance, height and wither, body length, skin thickness, neck portion, skin thickness at ribs, skin thickness at rump region. Four principal components explained a total variation of 69.522% with total variation of 28.678% was explained by first principal component. From this study it was clear that PCA is effective in producing number of variables to explain body conformation in Murrah buffalo.

The breeding values for birth weight, milk and reproductive traits of the Egyptian Buffalo were studied using PCA [20]. The traits used for the study included birth weight, weaning weight, gestation length, weight of dam, year of calving and parity. Eight principal components accounted for 70.37% of total variance with maximum share of variance accounted by first four principal components with individual variance of 25.71%, 18.20%, 13.28% and 13.18% respectively. The FactoMineR package in R software was used to carry out PCA.

Body measurement in male swamp buffalo of Indonesia was done using PCA and the morph metric traits underwent this study include ossa vertebrae cervicalis length, ossa vertebrae thoracicae length, ossa vertebrae lumbales length, ossa vertebrae sacrales length, os scapula length, os humerus length, ossa radius-ulna length, osmetacarpale length, os femoris length, ossa tibia-fibulla, length, osmetatarsale length, coxae distance, ischium distance, coxae-ischium distance, body length, withers height, chest depth, hip height. PCA was estimated using SPSS 16.0 software and measurement of sampling adequacy was done using KMO showing 0.24. Moreover, to evaluate the accuracy of factor analysis of data set Bartlett's test of Sphericity was used. A total five principal component were extracted, which explained a total variance of 70%. It was determined that the general performance of wither height, chest depth and hip height can be employed as morph metric selection criteria for swamp buffalo bulls at 3-4 age [21].

Principal Component Analysis in Goat

Morphological traits of Assam hill Goat in Eastern Himalayan, India were studied using PCA [22]. Traits studied include body weight, body length, height at withers, rump height, rump length, rump width, chest depth, heart girth, paunch girth, cannon bone length, cannon bone circumference, sacral pelvic width, shoulder width, height of sternum. A total of 85.84% variation was accounted by four principal components with highest correlation coefficient seen between body weight and body length. The software SPSS (2008) was used for the computation of the data to performed PCA. The measure of sampling adequacy was performed using KMO which showed same value as standard value that is 0.60 and Bartlett's test of Sphericity showed chi-square value 169.10.

Combine genetic merit for heat stress, fat and protein yield in Spanish Autochthonous Dairy Goat breeds was analyzed using PCA [23]. The main traits used in this study included total daily protein yield and total daily fat yield of three main Spanish dairy goats. Negative relationship was seen between total feed index and days in milk. Two Principal Components explained total variation of 89 to 98%. This study showed that PCA can be used for selection of animals that are more productive and better adapted to heat. The program MATLAB was used to obtain PCA score from calculated breeding value.

The mean of PCA was used to study biometric variability of Arabia goat in Laghouat [24]. The 14 traits used for study were head length, body length, neck length, ear length, hair length, rump length, tail length, head width, shoulder width, Ischia width, wither height, sacrum height, chest girth, canon circumference. The normality of data was verified by Shapiro wilk test and data was analyzed using R software version 3.3.1. A total variation of 60.50% was accounted by three principal components which has highest values of body length, height at withers, chest circumference and canon circumference. It was concluded that through these morphological indices, future selection of meat purpose goats can be done.

Principal Component Analysisin Sheep

Various traits including rump width, rump length, tail length, wither height, heart girth, body length, pouch girth, rump height, shoulder width, ear length, neck circumference, foreleg length, head length, rear leg length, horn length, neck circumference and length of hock were studied and PCA was used for the analysis of morph structure of Uda and Balami Sheep of Nigeria [25]. A total variation of 66.91% and 57.43% were explained by PC1 and PC2 respectively. The PC1 had its load on rump length, foreleg length, rear leg length, neck circumference, horn length and hock length and PC2 had its load on body length, rump width, rump length, tail length, shoulder width and head width. The sampling adequacy was tested using KMO test and results showed 0.923. It was higher than the standard value (0.60). Bartlett's test of Sphericity showed chi-square value of 2944.

Biometric traits were analyzed using PCA to explain body conformation in Kajali Sheep breed of Punjab, India [26]. Traits which were selected for this study were body length, height at wither, chest girth, paunch girth, ear length, face length, face width, tail length and adult body weight. A total variation of 68.66% was explained by three Principal Components. The PC1 explained 36% of total variation and describes mainly the body size. It had high load on chest girth, paunch girth and body weight. A total variation of 21% was explained by PC2 and had its main load on tail length, height and ear length. The software SPSS 2001 statistical package was used to carry out the analysis. The KMO test gave the measure of sampling adequacy as 0.736 which was higher than the standard value. The Bartlett's test of sphericity showed chi-square value as 1412.5.

PCA was performed to study the morph metric traits that explained morphological structure of Thali sheep [27]. The traits selected for this study included wither height, body length, head length, head width, ear length, ear width, neck length, neck width, heart girth, rump length, rump width, tail length, barrel depth, sacral pelvic width, birth weight, live body weight, teat length, teat diameter, testis length, testis width and scrotal circumference. The software SPSS 20.0 was used for PCA. There was high correlation between wither height, body length, heart girth and live body weight. The two principal components were found in females with a total variance of 66.02% and a total variance of 76.72 % wasaccounted by three principal components in males. Study showed that PCA can be used for improvement and future planning in breeding program.

Principal Component Analysis in Pigs

Comparative study was performed on reproductive traits and clustering analysis among different Pig breeds. The traits selected for the study were number of piglets born alive, frequency of still born piglets, total litter birth weight, average piglet birth weight, pre weaning mortality of piglets, number of weaned piglets, total weaning weight of litter and average weaning weight of piglet. Two principal components explained a total variance of 55% in pig's reproductive traits. PC1 who has significant load on total number of piglets born, number of piglets born alive and total litter birth weight explained a variation of 39.4%. PC2 who has its load on number of weaned piglets showed 29.7% of the total variance, total weaning weight of litter and average piglet weaning weight. The software STATISTICA (StatSoft Ltd.) software was used to carry out cluster analysis and PCA [18].

The assessment of litter traits in crossbred pigs was performed using PCA [29]. The two litter traits (birth, 4th week, 6th week and 8th week) were size and weight and data was collected from 42 weeks. The software used for PCA for litter trait was PROC PRINCOMP module of SAS 9.3 software. The validity of factor analysis of the data sets tested by Bartlett's test of Sphericity. There was significant correlation between majority of litter trait. There was a single principal component extracted for litter traits which accounted for 82.2% of total variance. Moreover, it has high load on litter size at 4th, 6th and 8th weeks. In breeding and selection program for reproductive traits this principal component can be utilized.

Body weight and morphological traits of two breeds of grower pigs were analyzed using PCA [30]. The traits analyzed in the study were body weight, head length, body length, body girth, hem length and ear length. The SPSS version 16 (2007) was used to carry out PCA. The sampling adequacy was tested by KMO and results showed 0.62 value which was almost equal to standard value. The Bartlett's test of Sphericity showed chi-square value 44.67. Three principal components were extracted that explained the total variation of 71.7% with PC1 showing a variation of 34.20%, PC2 showing a variation of 20.03% and PC3 showing a variation 17.47%. PC1 had high loads on body weight, head length, body length and ham length. From this study it can be concluded these principal components could help in selection and breeding program of pigs.

Principal component analysis in Poultry

Principal Component analysis was employed for the characterization of egg components in two Water Fowl Species. Various internal traits (yolk weight, albumen weight, and shell weight and yolk diameter) and external traits (egg weight, egg length, egg breadth and shell thickness) were selected for this study. Two Principal Components were extracted that accounted for 71.50% of total variance from duck. Similarly in geese two Principal Components were extracted which accounted for total variance of 80.19%. In duck PC1 showed positive load on egg length, egg breadth and moderate load on yolk diameter. PC2 showed positive load on shell thickness, egg breadth and moderate load on egg length. In geese PC1 showed a positive load on egg breadth, egg length and moderate load on egg shell thickness. PC2 showed positive load on egg shell thickness. For internal traits, two Principal Components were extracted from duck and geese showing a total variance of 82.86% and 95.09% respectively. PC1 in Duck showed positive load on albumen rate. Similarly PC2 showed positive load on shell weight whereas in Geese the PC1 showed positive load on shell albumen and weight of yolk. Software SPSS/PASW for windows version 19 was used for the factor analysis and sampling adequacy measured using KMO test which showed a value of 0.648 which was slightly higher than the standard value. From this study we can understand the reason of variation in weight of egg and its traits among the various species [31].

Another study was conducted on indigenous free range chickensin Kabwe, Zambia for the analysis of egg quality traits using PCA [32]. The trait selected for this study were similar with the traits selected by Amin *et al*., 2019 [31]. In addition to those traits, internal traits including albumen ratio, yolk height, yolk width, yolk ratio and yolk index were selected similarly additional external traits include were egg shape index, egg radius, egg surface area, shell weight and shell ratio. A total variance of 79% was collectively accounted by three Principal Components. PC1 accounted for a variation of 47.25%. It mainly includes egg weight, egg length, egg width, albumen weight, yolk width and yolk weight. A total variance of 18.94% was accounted by PC2, mainly focus on shell weight and shell thickness and PC3 obtained 12.86% of variance in total. It has positive effect on yolk weight and negative on shell thickness. The descriptive statistic of Minitab 18 was used to evaluate the various factors. The sampling adequacy was tested by using KMO and result showed 0.68 value which was higher than standard value. So, PCA was able to conclude how traits are related to each other for proper selection of high quality of eggs can be there through breeding program.

The morphological structures of indigenous Chicken were determined using PCA of body measurements. The traits employed were body weight, body length, back length, neck length, breast circumference, shank length, and shank circumference and toe length. Two principal components accounted for total variation of 63.9%. PC1 have larger share of breast circumference, body weight, body length and shank circumference. The PC2 had larger share of toe length, shank length and body length. The software SPSS 20 was used for the analysis of data and to obtain principal components. Varimax rotation was done to improve the interpretation of principal components. It concluded that traits such as breast circumference, body length and shank circumference can be used to estimate body weight of chicken [33].

The analysis of different economic traits in layer chicken was performed using PCA [34]. Various economic traits including weekly body weight from weekly body weight from 0 day to 20th week and 40th week, body weight at sexual maturity, age at sexual maturity, weight of first egg, egg production and egg weight at 40th week and 52nd week were studied. Total variance of 75.524% were explained by three principal components. PC1 had high loads on body weight 10th week to 20th week and body weight at sexual maturity with the variance of 38.892%. Similarly a variance of 27.072% and 9.560% were explained by PC2 and PC3 respectively. The SPSS 24 (2016) software was used for three PCA of various economic and reproductive traits. Bartlett's test of Sphericity was employed to test the validity of factor analysis which showed a positive result with value 300 and measure of sampling adequacy was done using KMO test value 0.954 which is higher than the standard value (0.6). This study showed that PCA can be used for the selection of various economic traits in layer chickens.

Applications of Principal Component Analysis

PCA has been used by various scientist of different fields and the earliest application is believed to be measuring components of human intelligence. Basically the intelligence quotient (IQ) is calculated by factor analysis of various test [35]. Residential differentiation of neighborhoods in a city was done on the basis of various characteristic and using factor analysis these characteristics were reduced to three [36]. Today these are known as social ranks, family size and ethnicity. Various indexes are developed on the basis of principal component analysis. The indexes like city development index and human development index are also formed by PCA. The variation in human gene frequencies across the regions was studied using PCA and data was summarized. Nowadays PCA is widely used in various population genetics and it is an important part of animal genetics, plant genetics and human genetics. PCA has been widely used in market research. It is used to produce customer satisfaction or customer loyalty scores for items and with clustering, to developed market groups that may be targeted with advertising campaigns [37]. Moreover, PCA has been a part of quantitative finance and even in the field of neuroscience [28] and it is playing a significant role.

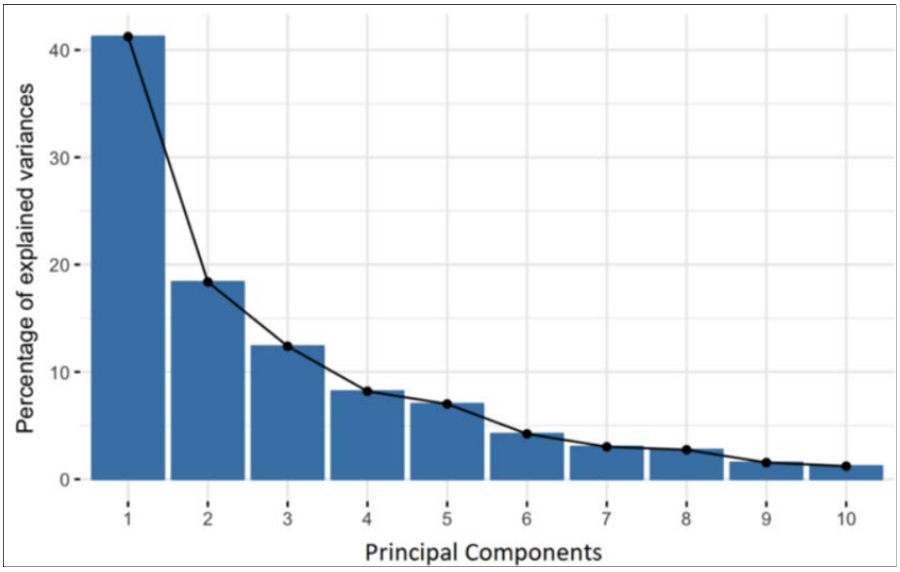

Fig 1: Percentage of Variance (Information) by each Principal Component [14]

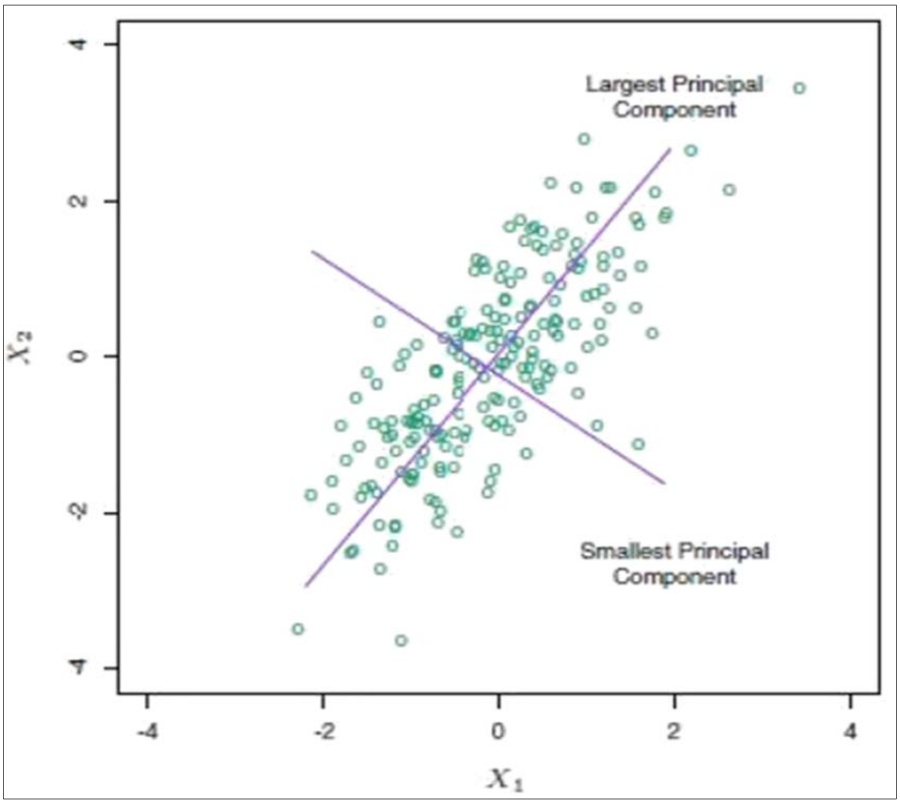

Fig 2: Showing Variation by different Principal Components [15]

Conclusion

PCA is widely used technique which helps in reducing the complexity of data and make it simple to understand and interpret. It has been widely used in various species of animals to predict the performance and helps in selection of future generation. Moreover, PCA is used in many disciplines. Various software have been developed for the analysis of PCA however, in this review it has been observed that most of the scientist prefer SPSS for computation of PCA. It was also observed most of the researches conducted in Asian continent, scientist carried out PCA using SPSS. PCA is able to summarize the data and is helpful in various breeding programmes. Till date various techniques developed however, PCA still remains widely accepted by large number of scientist.

Acknowledgement
As a researcher I can understand how difficult is to interpret and analyze a large set of data. However, PCA made it possible and I would dedicate this article to fellow researchers and future researchers and hope they will get benefit from this review paper.

Conflict of Interest
The author declare that they have no conflict of interest.

References
1. Jolliffe IT, Cadima J. Principal component analysis: a review and recent developments. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences. 2016 Apr 13;374(2065):20150202.
2. Wold S, Esbensen K, Geladi P. Principal component analysis. Chemometrics and intelligent laboratory systems. 1987 Aug 1;2(1-3):37-52.
3. Hotelling H. Simplified calculation of principal components. Psychometrika. 1936 Mar;1(1):27-35.
4. Girshick MA. Principal components. Journal of the American Statistical Association. 1936 Sep 1;31(195):519-28.
5. Girshick MA. On the sampling theory of roots of determinantal equations. The Annals of Mathematical Statistics. 1939 Sep 1;10(3):203-24.
6. Anderson TW. Asymptotic theory for principal component analysis. The Annals of Mathematical Statistics. 1963 Mar;34(1):122-48.
7. Gower JC. Some distance properties of latent root and vector methods used in multivariate analysis. Biometrika. 1966 Dec 1;53(3-4):325-38.
8. Rao CR. The use and interpretation of principal component analysis in applied research. Sankhyā: The Indian Journal of Statistics, Series A. 1964 Dec 1;26(4):329-58.
9. Craddock JM. A meterological application of principal component analysis. Journal of the Royal Statistical Society. Series D (The Statistician). 1965 Jan 1;15(2):143-56.
10. Jeffers JN. Two case studies in the application of principal component analysis. Journal of the Royal Statistical Society: Series C (Applied Statistics). 1967 Nov;16(3):225-36.
11. Abdi H, Williams LJ. Principal component analysis. Wiley interdisciplinary reviews: computational statistics. 2010 Jul;2(4):433-59.
12. Hair Jr JF, Black WC, Babin BJ, Anderson RE. Multivariate data analysis: A Global Perspective. p. 121-126.
13. Saikhom R, Sahoo AK, Taraphder S, Pan S, Sarkar U, Ghosh PR, Bhattacharya D, Baidya S. Principal component factor analysis of morphostructural traits of Haringhata black chickens. Indian Journal of Animal Health. 2017 Dec;56(2):211-8.
14. Jaadi Z. A step-by-step explanation of Principal Component Analysis (PCA). Retrieved June. 2021 Apr;7:2021.
15. Principal Component Analysis (tibco.com)
16. Buzanskas ME, Savegnago RP, Grossi DA, Venturini GC, Queiroz SA, Silva LO, Júnior RT, Munari DP, Alencar MM. Genetic parameter estimates and principal component analysis of breeding values of reproduction and growth traits in female Canchim cattle. Reproduction, Fertility and Development. 2013 Jun 24;25(5):775-81.
17. Verma D, Sankhyan V, Katoch S, Thakur YP. Principal component analysis of biometric traits to reveal body confirmation in local hill cattle of Himalayan state of Himachal Pradesh, India. Veterinary World. 2015 Dec;8(12):1453.
18. Tramonte NC, Grupioni NV, Stafuzza NB, Guidolin DG, Savegnago RP, Bezerra LA, *et al*. Genetic parameters, genetic trends, and principal component analysis for productive and reproductive traits of Guzera beef cattle. RevistaBrasileira de Zootecnia. 2019 Sep 12;48.
19. Dahiya SP, Kumar M, Dhillod S, Ratwan P. Principal component analysis of linear type traits to explain body conformation in Murrah buffaloes. Indian Journal of Animal Sciences. 2020 Nov 1;90(11):1546-50.
20. Salem MM, Nasr MA, Amin A. Principal component analysis of breeding values for birth weight milk and reproductive traits of the Egyptian buffalo. Tropical Animal Health and Production. 2021 Mar;53(1):1-7.
21. Putra WP, Hilmawan F. Principal component analysis (PCA) of body measurements in male swamp buffalo (*Bubalus bubalis*) of Indonesia. Journal of Applied Biological Sciences. 2022 Jan 23;16(1):70-9.
22. Khargharia G, Kadirvel G, Kumar S, Doley S, Bharti PK, Das M. Principal component analysis of morphological traits of Assam Hill goat in Eastern Himalayan India. JAPS: Journal of Animal & Plant Sciences. 2015 Oct 1;25(5):1251-1258.
23. Menéndez-Buxadera A, Muñoz-Mejías E, Sánchez M, Serradilla JM, Molina A. Use of Principal Component Analysis to Combine Genetic Merit for Heat Stress and for Fat and Protein Yield in Spanish Autochthonous Dairy Goat Breeds. Animals. 2021 Mar 8;11(3):736.
24. Laouadi M, Tennah S, Azzag N, Kafidi N, Antoine-Moussiaux N, Moula N. Biometric Variability of Arabia Goat in Laghouat (Algeria) Using the Mean of the Principal Component Analysis. Iranian Journal of Applied Animal Science. 2021;11(2):357-364.
25. Yunusa AJ, Salako AE, Oladejo OA. Principal component analysis of the morphostructure of Uda and Balami sheep of Nigeria. Int. Res. J Agric. Sci. 2013;1(3):45-51.
26. Mishra AK, Vohra V, Raja KN, Singh S, Yashwant S. Principal component analysis of biometric traits to explain body conformation in Kajali sheep of Punjab, India. Indian Journal of Animal Sciences. 2017 Jan 1;87(1):9398.
27. Akbar MA, Javed K, Faraz A, Waheed A. Principal Component Analysis of Morphometric Traits Explain the Morphological Structure of Thalli Sheep. Pak J Zool. 2021:1-6.

28. Jirsa VK, Friedrich R, Haken H, Kelso JS. A theoretical model of phase transitions in the human brain. Biological cybernetics. 1994 May;71(1):27-35.
29. Panda S, Gaur GK, Jena D, Chhotaray S, Tarang M, Wara AB. Principal component analysis of litter traits in crossbred piglets. The Pharma Innovation Journal. 2020;9(1):31-33.
30. Akporhuarho PO, Iriakpe O. Assessment of body weight and morphological traits of two breed of grower pigs using principal component analysis. Nigerian Journal of Animal Production. 2021 Nov 10;48(5):1-1.
31. Amin QA, Shaker AS, Akram SA, Saeed RB, Mohammed MS. Using Principal Component Analysis to Characterize Egg Components in two Waterfowl Species. Journal of Animal and Poultry Production. 2019 Oct 1;10(10):313-6.
32. Liswaniso S, Qin N, Xu R. Quantitative analysis of egg quality traits of indigenous free-range chickens in kabwe, zambia. J Entomol. Zool. Stud. 2020;8(2):603-08.
33. Vilakazi NB, Ncobela CN, Kunene NW, Panella F. Determining the morphological structure of indigenous chickens using multivariate principal component analysis of body measurements. Applied Animal Husbandry & Rural Development. 2020;13:69-75.
34. Sarma O, Dubey PP, Dash SK, Sahoo SK, Malhotra P. Principal Component Analysis of Different Economic Traits in. Agricultural Science Digest. 2022 April:1-6;D-5519
35. Kaplan RM, Saccuzzo DP. Psychological testing: Principles, applications, and issues. Cengage Learning; c2017 Jan 27.
36. Bloom L, Shevky E. The differentiation of an ethnic group. American Sociological Review. 1949 Aug 1;14(4):476-81.
37. DeSarbo WS, Hausman RE, Kukitz JM. Restricted principal components analysis for marketing research. Journal of Modelling in Management. 2007 Nov 6;2(3):305-328.