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Principal Component Analysis of Economic Traits in HD-K75 Pig, A Crossbred Pig Variety of India

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ABSTRACT

Background: Principal component analysis (PCA) is a biometrical technique or a dimensionality reduction method where large number of measurements could be replaced by fewer measurements without significant loss of information. PCA is a multivariate methodology and helps to eliminate redundant traits and transforms original group of variables into another group known as principal components. It can be used with success when characteristics are correlated. PCA can help in accurate selection of superior animals.

Methods: The present study was carried out in HD-K75 pigs maintained at ICAR-All India Coordinated Research on Pig, AAU, Khanapara, Guwahati, Assam, India. A total of 13 economic traits *viz*. age at sexual maturity (ASM), age at first fertile service (AFFS), age at first farrowing (AFF), farrowing interval (FI), litter size at birth (LSB), litter weight at birth (LWB), litter size at weaning (LSW), litter weight at weaning (LWW), teats number (TN), body weight at Birth (BWB), body weight at weaning (BWW), body weight at 5 month (BM5) and body weight at 8 month (BM8) were considered. Data were collected from a total of 164 sows. Data belonged to 8 years from 2015 to 2023. The principal component analysis was performed using the factor module in SPSS 24.

Result: Factor analysis with varimax rotation uncovered four principal components, collectively explaining 84.18% of the total variance. The first, second, third and fourth principal component accounted for 29.71%, 29.33%, 12.683% and 12.452% of the variance. High component loading was found for LSW and LWW in first component, LSB for second component, BW5 for third component and BW8 for fourth component respectively. The communality values ranged from 0.980 (ASM and AFFS) to 0.608 (BWW). These findings indicate that PCA can serve as a valuable tool in breeding programmes, allowing for a significant reduction in the number of economic traits to be used in selection procedure.

Key words: Correlation, Economic traits, HD-K75, Principal component analysis.

INTRODUCTION

As the swine industry continues to explore pork quality traits alongside growth, feed efficiency and leanness, it is essential to understand the genetic relationships underpinning these characteristics. With the growing emphasis on multiple desirable traits, animal breeders must develop effective strategies for making direct genetic improvements for each trait and evaluate alternative selection indices incorporating various phenotypic measurements (Green *et al.,* 2024). Compared to other livestock, pigs contribute quicker economic return to farmers. They are among the most prolific and rapidly growing animals, capable of efficiently converting food waste into valuable products. Pig production is relatively cost-effective due to rapid growth rates, high production potential, excellent carcass yield efficiencyand strong adaptability to diverse environmental conditions (Panda *et al.,* 2020). Rapid advancements in research have significantly increased the volume of large data sets, presenting challenges in timely and accurate data interpretation. To address these challenges, various techniques have been developed, among which Principal Component Analysis (PCA) stands out as a commonly used method (Jolliffe and Cadima, 2016). PCA is a multivariate statistical technique used for dimensionality reduction in data analysis. It transforms a set of correlated variables into a smaller set of uncorrelated variables called principal components, capturing the most significant features of the data while reducing the redundancy of the datasets.

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PCA can be used for data simplification, reduction, classification, variable selectionand more (Wold *et al*., 1987). Its primary goal is to extract critical information from data and represent it through a series of summary indices known as principal components (PC1, PC2, PC3, *etc*.). The principal component that accounts for the highest variance in the data is designated as the first principal component (PC1). The second principal component (PC2) represents the next most significant source of variation. Together, these two principal components form a plane that can be visualized graphically. In PCA, the extent of variance explained by each principal component is typically quantified and visualized using a scree plot. PCA involves the computation of eigen values and eigen vectors of the data's covariance matrix. The eigen values quantify the variance accounted by each principal component, whereas the eigenvectors indicate the direction of each principal component within the dataset. Therefore, PCA is a powerful tool for simplifying and analyzing complex datasets, making it indispensable in various fields.

Though the state of Assam alone has a pig population of 2,099,000 (Twentieth Livestock Census, 2019), there lies a gap between the production and requirement of meat. The annual pork consumption by 30% of total population of Assam (*i.e*. 1.03 crore) is 11.07 crore kg. On the other hand, the annual pork production of the State is 1.87 crore kg. This clearly demonstrates that there is a shortfall of 9.20 crore kg of pork meat or 15,57,146 pigs, annually. (https://www.sentinelassam.com, Dated 6th August, 2021). This underlying gap may be due to the fact that the production performance of the pigs which are being reared is not getting momentum due to lack of quality germplasm, scientific selection and breeding, superior breeding stock, genotypic and phenotypic data, genetic testing, scientific management of pigs, *etc*. To address this, the initial and foremost step is farming of quality and genetically superior animals ensuring enhanced performance efficiency. To meet up this, a new variety of pig called HD-K75 (75% Hampshire and 25% Desi), has been developed by ICAR-All Indian Coordinated Research project (AICRP) on Pig, Assam Agricultural University, College of Veterinary Science, Khanapara, Guwahati, Assam, India, which has been introduced in the villages helping rural pig farmers of Assam as well as nearby northeastern states. These animals have already proved to be well adapted to the prevailing conditions of Assam and gaining popularity too. The animals are maintained in the nucleus herd that is AICRP on Pig, Khanapara, Assam and it is being transmitted to the commercial herd or farmers field. Hence, prioritization is needed for precise and early selection of superior animals for production of best progenies to be transferred to field level. This can be achieved by implying different biometrical concepts, newer statistical techniques, reproductive biotechnologies particularly marker assisted selection (MAS), *etc*. It is envisaged that the Principal Component Analysis approach can be adopted at farm level for accurate selection of best performing animals. This will enable dissemination of superior quality germplasm (HD-K75) from farm to field level. Keeping in view of this the present study has been carried out for the Principal Component Analysis of Economic Traits in HD-K75 Pig maintained under ICAR-AICRP on Pig, AAU, Khanapara, Assam, India.

MATERIALS AND METHODS

Description of data

For the present investigation, data reflecting the performance of HD-K75 pigs maintained under ICAR-AICRP on pigs, AAU, Khanapara were utilized. Data were collected from 164 sows of the farm. The data belonged from 16th generation to 19th generation (four generations) from the year 2015 to 2023. Each generation comprised of three crops or farrowing which occurs in duration of 2 years.

Data collection

For the present investigation, the data of following traits collected.

Traits (unit)	Abbreviation
Age at sexual maturity (days)	ASM
Age at first fertile service (days)	AFFS
Age at first farrowing (days)	AFF
Farrowing interval (days)	FI
Litter size at birth (number)	LSB
Litter weight at birth (kg)	LWB
Litter size at weaning (number)	LSW
Litter weight at weaning (kg)	LWW
Teats numbers	TN
Body weight at birth (kg)	BWB
Body weight at weaning (kg)	BWW
Body weight at 5 month (kg)	BW5
Body weight at 8 month (kg)	BW 8

Statistical analysis

The phenotypic correlations between economic traits were computed by using Pearson's correlation method (Snedecor and Cochran, 1967). Traits exhibiting high correlation were subsequently analyzed using multivariate principal component analysis. The aim of principal component analysis is to capture the maximum proportion of variance from the original set of variables while minimizing the number of composite variables. This approach assumes that the communalities (common variance) represent a small fraction of the total variance. Varimax rotation was applied to the principal components to transform them into a simpler structure. To assess whether the dataset, which included 1,163 animals and thirteen traits, was suitable for factor analysis, Bartlett's test (1950) was initially performed, in accordance with the recommendation by Maxwell (1959). The dataset's validity was further confirmed at a 1% significance level using the Kaiser-Meyer-Olkin (KMO) test for sampling adequacy. To determine the number of factors, the criterion established by the Kaiser rule (Johnson and Wichern, 1982) was used, retaining

only factors with eigen values greater than 1. The suitability of the common factor model was evaluated using Kaiser's measure of sampling adequacy (MSA), with an MSA below 0.5 considered as unacceptable. Principal component analysis, as described by Everitt *et al.* (2001), is a method for converting variables in a multivariate dataset (X_1, X_2, ..., X_n) into a set of uncorrelated variables (Y_1, Y_2, ..., Y_n). These new variables explain a reduced proportion of the total variance present in the original variables specified as:

$$Y_1 = a_{11}X_1+a_{12}X_2+...+ a_{1n}X_n$$
$$Y_2 = a_{21}X_1+a_{22}X_2+...+ a_{2n}X_n$$
$$Y_n = a_{n1}X_1+a_{n2}X_2+...+ a_nX_n$$

The principal components Y_1, Y_2, ..., Y_n capture reduced portions of the overall variance observed in the original variables X_1, X_2, ..., X_n. To enhance the interpretability of the extracted principal components, orthogonal rotation was applied, which aimed to maximize variance in the linear transformation of the factor pattern matrix. The principal component analysis was performed using the factor module in SPSS 24.

RESULTS AND DISCUSSION

Phenotypic correlation

In the present study the magnitude of correlation coefficient ranges from -0.658 to 1.000 (Table 1). Highly significant positive correlation found between reproductive traits *viz.* ASM with AFFS and AFF and between AFF and AFFS. Similar finding of strong positive correlation between AFS and AFF was exhibited in Large White pig (Yu *et al.,* 2022). Highly significant negative correlation was reported between FI with ASM, AFFS and AFF. Significant effect of BWB with FI; BW5 with LSW and LWW and BW8 with TN was also observed. Highly significant correlation between litter traits such as LSB with LWB, LSW and LWW and between LWB with LSW and LWW were observed in the present study. Similar observations of high and positive correlation between the litter traits in Hampshire×Indigenous pigs was reported by Phookan *et al.* (2013). Also, Nowak *et al.* (2020) reported strong positive correlations between the litter-related traits that was between litter size and the number of piglets born alive (0.90), the number and the percentage of piglets born alive (0.88), the numbers of piglets born alive and weaned (0.78) and litter size and the number of weaned piglets (0.68) in Polish Large White, Polish Landraceand Yorkshire, Duroc, Berkshire and Hampshire animals kept on farms located in Poland and in the United States. Further, comparable observation of high and positive phenotypic correlations among the litter traits was revealed by Panda *et al.* (2020) in crossbred pigs and Bayan, 2022 in HD-K 75 pigs. Strong positive genetic correlations between litter size from farrowing to weaning were found in black pigs of Taiwan (Lee *et al*., 2022). High and positive phenotypic correlation obtained in the present study suggested that piglets having larger litter size at birth is suggestive of larger litter size at weaning, higher litter weight

Table 1: Phenotypic correlation coefficients among different economic traits.

Traits	ASM	AFFS	AFF	FI	LSB	LWB	LSW	LWW	TN	BWB	BWW	BW 5	BW 8
ASM	1	1.000**	1.000**	-0.656**	0.097	0.159	-0.181	-0.228	-0.130	-0.232	0.070	-0.195	-0.055
AFFS	1.000**	1	1.000**	-0.656**	0.096	0.158	-0.185	-0.232	-0.130	-0.231	0.069	-0.195	-0.055
AFF	1.000**	1.000**	1	-0.658**	0.095	0.157	-0.188	-0.238	-0.130	-0.233	0.069	-0.197	-0.057
FI	-0.656**	-0.656**	-0.658**	1	0.026	0.025	0.296	-0.254	-0.115	0.509*	0.158	0.186	0.137
LSB	0.097	0.096	0.095	0.026	1	0.879**	0.929**	0.876**	0.187	-0.165	-0.106	0.141	0.010
LWB	0.159	0.158	0.157	0.025	0.879**	1	0.792**	0.723**	0.181	0.022	-0.050	-0.045	0.048
LSW	-0.181	-0.185	-0.188	0.296	0.929**	0.792**	1	0.950**	0.238	-0.033	-0.052	0.045	0.045
LWW	-0.228	-0.232	-0.238	0.254	0.876**	0.723**	0.950**	1	0.192	-0.27	-0.099	0.405*	0.064
TN	-0.130	-0.130	-0.130	-0.115	0.187	0.181	0.238	0.192	1	-0.256	-0.098	0.417*	0.332*
BWB	-0.232	-0.231	-0.233	0.509*	-0.165	0.022	-0.033	-0.027	-0.256	1		-0.300	0.041
BWW	0.070	0.069	0.069	0.158	-0.106	-0.050	-0.052	-0.099	-0.098	-0.027	1		-0.217
BW 5	-0.195	-0.195	-0.197	0.186	0.141	-0.045	0.405*	0.417*	-0.300	-0.047	-0.043	1	-0.077
BW 8	-0.055	-0.055	-0.057	0.137	0.010	0.048	0.045	0.064	0.332*	-0.041	-0.217	-0.077	1

Coefficients of correlation (below diagonal) with their standard errors (above diagonal).
**Correlation is significant at 0.01 level, *Correlation is significant at 0.05 level

Table 2: KMO and bartlett's test.

Kaiser-Meyer-Olkin	Measure of sampling adequacy	0.659
	Approx. Chi-square	442.809
Bartlett's test of sphericity	Df	78
	Sig.	.000

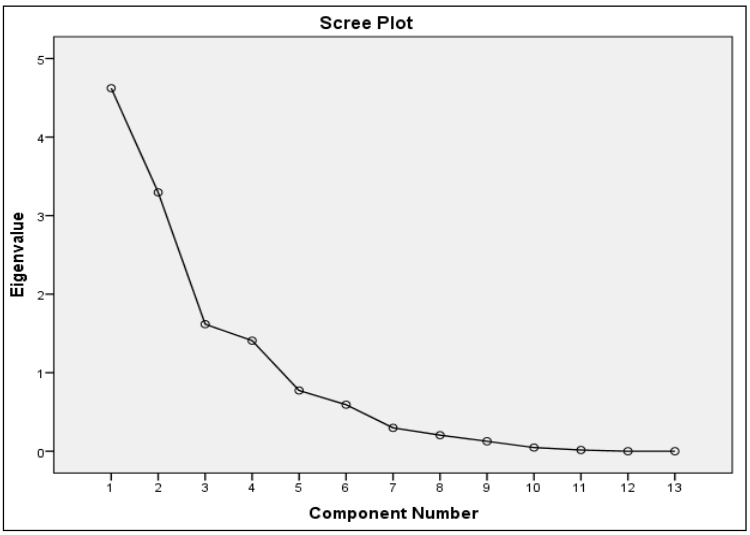

Fig 1: Scree plot showing component numbers with eigen values.

at birth and higher litter weight at weaning. This justify scope of genetic improvement of litter traits by favoring the selection for larger litter size at weaning and higher litter weight at weaning based on the superiority of litter size and weight of the piglets at birth. However, Pandey and Singh, (2010) observed that litter size at birth had negative correlation with litter size at weaning, litter weight at birth and weaning in Landrace, Desi and their cross-bred pigs. Also, the phenotypic correlation of litter size at weaning with litter weight at birth and at weaning and farrowing interval had negative and non-significant effect. They found litter weight at birth had negative phenotypic correlation with litter weight at weaning.

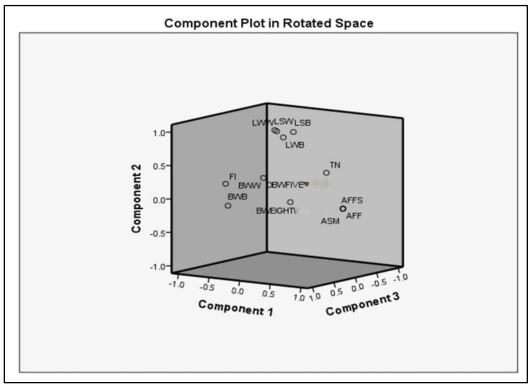

Fig 2: Component plot in rotated space showing six different components.

Principal component analysis

Principal component analysis was applied to thirteen different economic traits in HD-K75 pig. The Kaiser-Meyer-Olkin method yielded a measurement of sampling adequacy of 0.659 (Table 2) whereby eigen values more than 1 were considered. This value assesses the adequacy of the data for each factor in providing reliable results for PCA. The measure of sampling adequacy below 0.5 is considered to be inadequate (Khargharia *et al.,* 2015). The varimax rotation method was employed to maximize the sum of loading squares (Fernandez, 2002). Bartlett's test of sphericity was applied to assess the significance of the correlation matrix. The resulting chi-square value was highly significant (P<0.01), measuring 442.809 (Table 2). The sum of squared loadings were extracted by PCA, variation explained by each component (Table 3) and Eigen values are given in Fig 1. Four, out of the thirteen components were selected using the Kaiser Rule Criterion (Johnson and Wichern, 1982) to determine the significant number of components. The cumulative variance of 84.18% (Table 3) was accounted by four principal components (PC1, PC2, PC3 and PC4), each with eigen values more than 1. The variance of each trait was as per explained by PCA (Mavule *et al.,* 2013). The component plot in rotated space depicts the distribution of the eight components, as illustrated in Fig 2.

In the present study, the first principal component (PC1) explained for 29.71% of the total variance (Table 3). PC1 represented by a very high component loading for LSW and LWW in HD-K75 pig. The second principal component (PC2) explained for 29.33 % of total variance. PC2 showed high loadings on LSB. The third principal component (PC3) explained 12.68% of total variance which described high

Table 3: Total variance explained by different factor.

Component	Initial eigen values			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	4.622	35.556	35.556	4.622	35.556	35.556	3 .863	29.713	29.713
2	3.296	25.353	60.910	3.296	25.353	60.910	3.813	29.333	59.046
3	1.618	12.444	73.353	1.618	12.444	73.353	1.649	12.683	71.729
4	1.408	10.828	84.181	1.408	10.828	84.181	1.619	12.452	84.181
5	.773	5.947	90.128						
6	.592	4.556	94.684						
7	.298	2.289	96.974						
8	.205	1.574	98.547						
9	.126	.973	99.520						
10	.047	.361	99.882						
11	.015	.117	99.998						
12	.000	.001	100.000						
13	5.899E-005	.000	100.000						

loads on BW5. The fourth principal component (PC4) explained for 12.45% of total variance which described high loads on BW8. Table 4 represents the coefficient of principal component analysis of rotated component matrix. The different weights were assigned by PC1, PC2, PC3 and PC4 showing different component loadings in HD-K75 pig. PC1 represented highest variance. Yakubu *et al.* (2009) in Fulani cattle, Pundir *et al.* (2011) in Kankrej cows, Yunusa *et al.* (2013) in Balami and Uda sheep, Tolenkhomba *et al.* (2013) in Mizo local pigs, Khargharia *et al.* (2015) in Assam hill goat and Okoro *et al.* (2015) in crossbred pigs of Nigeria also reported that the first factor explained maximum variation. Okoro *et al.* (2015) in crossbred pigs of Nigeria extracted two factors of 6 body confirmation traits at pre-weaning stage which accounted for 91.63% of total-variation. They however extracted only one factor at post-weaning stage explaining 73.63% of the total variation. Tolenkhomba *et al.* (2013) reported a single factor of 5 body measurements which was extracted by at birth, 4 week weaning, 14 week and 18 week which accounted 60.41, 69.79, 67.49, 81.85 and 87.73% of total variance in Mizo local pigs. Kramarenko *et al.,* (2018) observed three principal components (PC) which accounted for near 80% of the dependency structure.PC1 accounted for 33.6% of the total variance and was influenced by total number of piglets born (TNB) and number of piglets born alive (NBA); PC2 accounted for 27.1% of the total variance and linked to NBA (positive), number of stillborn piglets (NSB) and frequency of stillborn piglets (FSB) (negative) and PC3 accounted for 18.7% of the total variance and contrasted sows having large number of weaned piglets and low pre-weaning mortality in piglets with sows having small number of weaned piglets and high pre-weaning mortality in piglets. Panda *et al.* (2020) could extract 3 PCs at 4 week, 2 PCs at 6 week and 2 PCs at 8 week in crossbred pigs which had more than 1 eigen values and explained 74%, 74% and 75% of total variance. PC1 was represented by heart girth and body length, PC2 by height at shoulder and height at foreleg and PC3 by snout circumference. However, Panda *et al.* (2020) in another study on liter size of crossbred pigs reported a single PC which was extracted with an Eigen value greater than 1. It accounted for 82.24% of total variance. PC1 was characterized by litter size at 4, 6 and 8 week. This factor seemed to be representing the overall performance of the litter.

The communality values ranged from 0.980 (ASM and AFFS) to 0.608 (BWW) across all economic traits (Table 5). The trait like BWW had lower communality indicating that this trait is less effective in explaining the performance in HD-K75 pig and traits including ASM, AFFS, AFF, LSB, LSW, LWW showed high communalities indicating that these traits will be effective in breeding programmes for selection of HD-K75 pig.

CONCLUSION

The study suggests that principal components provide an effective approach for selecting animals by considering a

Table 4: Varimax rotated component matrix showing different component loadings in HD-K75 pig.

Traits	Component			
	1	2	3	4
ASM	-.783	.562	.212	.079
AFFS	-.787	.558	.208	.079
AFF	-.785	.561	.202	.078
FI	.619	-.421	.016	.519
LSB	.589	.777	-.006	-.030
LWB	.658	.610	.031	-.099
LSW	.752	.607	-.072	.184
LWW	.726	.616	-.062	.153
TN	-.103	.327	-.844	.112
BWB	.372	-.513	.382	.355
BWW	.507	.051	.422	-.412
BW five months	.099	.283	.644	.359
BW eight months	-.319	.037	-.167	.783

Table 5: Communalities of different traits.

Traits	Extraction
ASM	0.980
AFFS	0.980
AFF	0.978
FI	0.830
LSB	0.951
LWB	0.816
LSW	0.973
LWW	0.933
TN	0.843
WB	0.673
BWW	0.608
BW 5	0.633
BW 8	0.744

set of inter-correlated variables. A total of four PCs have been extracted from a total of 13 economic traits considered. These components determine the underlying source of shared variability in explaining the performance in HD-K75 pigs. PC1 had the largest share of overall variance (29.71%) which has high loading on LSW and LWW followed by PC2, PC3 (29.33%, 12.68% and 12.45%) of the total variance. PC2 showed high loadings on LSB. PC3 described high loads on BW5. PC4 explained high loads on BW8. The percentage of cumulative variance accounted for 84.18%. Thus, the four main components extracted could be used inbreeding programmes with reduction in the number of economic traits to be recorded for explanation of maximum variability for prediction of performance in HD-K75 pigs. This can lead the selection procedure to be more accurate and also time and labour saving.

Conflict of interest

The authors declare that there are no conflict of interest.

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