Smart Agricultural Technology 7 (2024) 100432

Contents lists available at ScienceDirect

Smart Agricultural Technology

journal homepage: www.journals.elsevier.com/smart-agricultural-technology

Evaluation of experimental error in accelerometer monitoring: Variation among individual animals versus variation among devices

Colin Tobin [a,*], Derek Bailey [b], Caroline Wade [b], Ly Ly Trieu [c], Kelsey Nelson [b], Cory Oltjen [b], Huiping Cao [c], Tran Cao Son [c], Victor Flores [b], Briza Castro [b], Jennifer Hernandez Gifford [b], Mark Trotter [d], David Kramar [e]

[a] Carrington Research Extension Center, North Dakota State University, Carrington, ND 58421, USA
[b] Department of Animal and Ranges Sciences, New Mexico State University, Las Cruces, NM 88003, USA
[c] Department of Computer Science, New Mexico State University, Las Cruces, NM 88003, USA
[d] Institute for Future Farming Systems, School of Health, Medical, and Applied Sciences, CQUniversity, Rockhampton, QLD, Australia
[e] Center for the Environment and Society, Washington College, Chestertown, MD 21620 USA

ARTICLE INFO

Edited by: Dr Spyros Fountas

Keywords:
Accelerometer
Movement intensity
Movement variation
Random forest

ABSTRACT

Application of sensors is becoming prevalent in research and production settings. With increasing battery power, improved case and component durability, and consistent data connectivity, precision technologies, such as accelerometers, can help identify changes in livestock behavior. The objective of this study is to identify the variation among individual animals and among different accelerometer devices. A repeated 4 × 4 Latin-square design was utilized to identify differences between accelerometer, animal, and week. Twelve ewes separated into three age groups were randomly assigned to 4 different accelerometers deployed as an ear tag weekly over the course of 4 weeks. Manual behavior observations were paired to calculated accelerometer metrics and were used for training and validation dataset to predict animal behavior using random forest machine learning. Movement variation had the greatest importance in predicting behaviors. Across the four week study, differences were found for animal and week through each of the calculated metrics. Differences in accelerometers were detected for 80 % of the calculated metrics. This study shows the importance to account for variation among individual animals and accelerometer devices in experimental designs.

1. Introduction

Advancements in technology have improved methods for remotely monitoring livestock. Accelerometers have been utilized by researchers to detect changes in animal behavior resulting from health and welfare issues in several livestock industries including sheep [4,13,14,16,18,19,21,36], dairy cattle [2,25,26,32], and beef cattle [6,10,34,35]. Accelerometers that provide activity data in "real time" or "near real-time" are becoming commercially available and give livestock producers the ability to remotely monitor animal health and movement and to expedite treatment and improve animal well-being ([1,17,18,33]).

Accelerometers are electronic sensor systems capable of detecting changes in activity by measuring linear acceleration along three axes in units of the acceleration of gravity (-9.8 m s^{-2}) [3,39]. Acceleration measurements along the X (horizontal), Y (longitudinal), or Z (vertical) axes are interpreted as animal motion and can serve as a proxy for energy expenditure [29]. Multiple studies have utilized accelerometers to study multiple livestock behaviors including lying, standing, grazing, and walking [11,23,27]. Machine learning is often used to predict livestock behavior and livestock well-being concerns from the multi-axis accelerometer data [10,21]. Disease [6,20,35], lameness [4,7], parturition [16,19], and water failure leading to deprivation [34] can affect animal movement and activity, which allows accelerometers to be used to remotely monitor livestock for these welfare concerns. Supervised machine learning techniques, such as random forests, incorporate observed individual behavior data to train and validate the prediction algorithm. Prediction models can have high misclassification rates [35] and low accuracy [19], even with large observation datasets. Development of algorithms that can detect changes in behavior and associated well-being concerns and production issues such as disease, parturition

Abbreviations: MI, movement intensity; MV, movement variation; ROP, receiving operator characteristics; SMA, signal magnitude area.

* Corresponding author.
E-mail address: colin.tobin@ndsu.edu (C. Tobin).

https://doi.org/10.1016/j.atech.2024.100432
Received 6 October 2023; Received in revised form 2 March 2024; Accepted 3 March 2024
Available online 3 March 2024

and estrus is essential for the use of on-animal sensor and tracking to be successful [1,37].

One issue that may affect monitoring and evaluation of behavior with accelerometers is variation in recorded movements among individual animals. The intensity of a behaviors (i.e., walking) of one individual may differ greatly from the intensity of other in the herd, which could cause difficulty in prediction of behavior if a group of individuals are pooled together for analysis. A second problem is the potential for variation among the accelerometer devices. Movement intensity of two accelerometers on the same individual may not be identical. Anecdotal observations of variation among different accelerometers monitoring the same heifers was observed by Tobin et al. [35]. Although diurnal movement patterns of healthy heifers remained similar across time, mean values of movement intensity (a metric summarizing movement across 3 axes) changed when different accelerometer devices were placed on heifers each week. This suggested that not only does activity monitored by accelerometers likely vary among individual animals, but it also could vary among the accelerator devices. Chang et al. [10] demonstrated that an algorithm developed for the individual animal was more accurate than one developed over a group further supporting this hypothesis. However, several commercial sensors (e.g., Cowmanager SensOor (https://www.cowmanager.com/) and smaXtec (https://smaxtec.com) use the same algorithm for all the animals in the herd, which potentially could reduce the accuracy of predictions if there is inherent variation in intensity of movements among animals and sensors. In addition, both sources of variation could create experimental error that would affect accuracy of behavior predictions from machine learning Experimental designs to control or minimize these two sources of experimental error (variation among individual animals and variation among accelerometer devices) depends on the magnitude and pattern of these two potential factors affecting the movement data.

Numerous metrics can be calculated from accelerometer data [15], and machine learning techniques can be used to find the best metrics to use for prediction of behavior. However, it is also important to understand the relationship between the accelerometer metric and behavior. Some metrics may have characteristics that make them more robust than others.

This study aims to document and evaluate variation among individual animals and among accelerometer devices in movements recorded by accelerometers. Variability among animals and accelerometers potentially can affect behavior prediction models leading to lower accuracy and less effective algorithm identification of animal behaviors and welfare concerns from remotely collected accelerometer data if the same algorithm is used for groups of livestock, which is simpler approach to use for commercial applications. Accuracy of prediction models is the key or expediting intervention and treatment to ensure the highest levels of animal welfare. If the same algorithm is to be used on different animals and devices, the calculated metrics from the accelerometer used should be robust and less sensitive to variation that may occur across the herd. In addition, livestock research involving accelerometers could use experiment design that account for variation among individual animals and accelerometer devices if the differences are elucidated and quantified.

2. Materials and methods

2.1. Site and animals

All procedures were approved by the New Mexico State University Institutional Animals Care and Use Committee (2019-007).

This study was conducted on the campus of New Mexico State University in Las Cruces, New Mexico, USA at the West Sheep Unit research facility. Twelve mature ewes ages 1 to 3 yr ($n = 4$ per age group) were housed in a single pen (18.3 × 9.1 m) and monitored from 23 August to 20 September 2021. Each ewe was fed 1.6 kg of alfalfa hay in the morning (0800 h) with ad libitum access to water, mineral, and salt.

2.2. Accelerometers

A tri-axial Axivity AX3 MEMS accelerometer (Axivity Ltd, Newcastle, UK) was attached to an Allflex ear tag (Allflex USA Inc., DFW, TX, USA) with shrink wrap tubing. The ear tag with the accelerometer was attached to the pinna of the left ear. Accelerometers were charged prior to deployment to last a minimum of 30 days (study duration). Accelerometers were configured to collect acceleration signals at a sample rate of 12.5 Hz measuring longitudinal movements of the horizontal X-axis (left and right), longitudinal Y-axis (forward and backward), and vertical Z-axis (up and down). The dimensions of each accelerometer were 23 × 32.5 × 7.6 mm and weighed 11 g. For a detailed image of accelerometer location and orientation, please see Gurule et al. [19].

Accelerometer movements were subsequently stored on the NAND Memory within the device. Accelerometers were removed weekly and after the study to retrieve data via USB connection to the OmGui Axivity computer software. The OmGui program downloads data from the accelerometer, allows for manipulation for desired study period, and stores raw data as a .CWA file, not compatible with Microsoft Excel (Microsoft Corporation, Redmond, WA, USA). No accelerometers failed throughout the course of the study. The internal clock was synced within the OmGui program with the time.is website (https://time.is) prior to deployment. Data were aggregated into 1 min epochs.

2.2.1. Data collection and behavior observation

Accelerometers were removed from each animal every Monday (23 August, 30 August, 6 September, 13 September) during the four-week study by cutting the male button attaching the tag to the ear. The accelerometer was not removed from the Allflex ear tag. The accelerometers remained attached to the tag using the heat shrink tubing. During weeks 2–4, ear tags were removed from the ewe, data were downloaded and accelerometers were reset for preparation for the next weeks' placement. No alterations of the tags were made throughout the study. Tags were reattached to the ewes using a new male Allflex pin and the original hole made in the left ear. This protocol allowed the accelerometers to be move from one ewe to another with the ear placement and tag orientation as similar as possible. Ear tags are usually the preferred approach for producers to remotely monitor their livestock compared to collars and other methods of attaching sensors to animals [38].

To accommodate changing ear tags each week, no observations were recorded on Mondays or Tuesdays during the study. Behavioral observations were recorded from Wednesday to Sunday each week during the trial. Behavior observations were recorded by trained observers with behaviors including lying, standing, feeding, nibbling on the ground (stereotypic behavior similar to feeding). Observers time recording devices were synced with the time.is website (https://time.is) prior to deployment.

Feeding was defined as the ewe consuming feed from the bunk, chewing with head up or down while standing or moving. Lying was defined as ewe resting on the ground with no spatial movement but could be ruminating. Standing was defined as ewe on all legs in contact with the ground with no spatial movement but could be ruminating. Lying and standing behaviors were grouped into non-active while feeding and nibbling were grouped into active. Behavioral observations were aggregated into 1 min epochs and behaviors that were recorded that began or ended during the minute were excluded from analysis. In total, 2322 full 1 min epochs of observed behavior were recorded and used in the analyses. This is equivalent to a total of 38.7 h of observation across the five observers

2.3. Experimental design

This study was designed as a repeated Latin-square. Three 4 × 4 Latin-squares were designed to accommodate ewes born in 2018 (ewes 801, 811, 818, 831), 2019 (ewes 907, 914, 919, 950), or 2020 (ewes

009, 014, 017, 019). Four ewes born during each year were randomly selected from the herd and used in the Latin square design for that year of birth. Limiting a 4 × 4 Latin square to ewes born in a given year helped reduce the effect of age on the analyses, and evaluating 3 age groups should make the results more representative of commercial sheep herds. For each year the fixed effects for the Latin square were ewe, accelerometer and week (Table 1). Assignments of ewes to accelerometers each week were made randomly according to the Latin square design.

The use of Latin-square design allows the simultaneous evaluation of the fixed effects of ewe, accelerometer, and week. The error term from the Latin-square design does not permit the evaluation of interactions between the fixed effects, Table 1) [31]. Fitting interactions between fixed effects interaction would result in the incorrect error term [40]. To limit any interaction between fixed effects, the authors intentionally utilized the same hole which was produced from tagging the animal. The exact same attachment point of the Allfex tag/accelerometer allowed us compare different accelerometers on the same ewe.

2.4. Development of behavior classification algorithm

The mean, maximum, minimum, and standard deviation were calculated for each 1 m epoch from accelerometer axes. Additionally, movement intensity (MI), signal magnitude area (SMA), entropy, energy, and movement variation (MV) were calculated as metrics for behavior analysis. A total of 19 metrics were calculated for each 1 m epoch amended from Fogarty et al., 2020 and [15,36] (Tables 2, 3).

2.5. Machine learning analyses

Random Forest machine learning was used to create behavior predictions from a training dataset and validate the predications from a separate and independent data set. Shaikhina et al. [28] developed a prediction model with 85 % accuracy with only 80 data points using this technique. Random Forest have also shown to have strong predictive performance with imbalanced datasets [8]. Only the calculated metrics were used for predictive variables (features) for machine learning analyses. These predictive variables were MI, SMA, Energy, Entropy and MV. The number of predictor variables was limited to help insure that the machine learning model was not overfitted. Random forests models were created in R (R Development Core Team, 2011) using 'randomForest' library. Of the 2322 observed behaviors, 1870 random observation (80.53 %) were used as the training dataset while the remaining 452 observations (19.46 %) were utilized as the validation dataset. The ntree was set to 300 after being reduced from 500 and mtry was 4. Mean Decrease Accuracy and Mean Decrease Gini were plotted from the random forest model to determine importance of each calculated metric. Mean Decrease Accuracy expresses how much of the model accuracy would be lost by excluding each variable. Mean Decrease Gini identifies how each variable accounts for the homogeneity of the nodes within the grown trees [24]. One-minute epochs of predicted active behavior were compiled into daily percentages of active behavior.

Table 1
Structure of repeated Latin-squares.

		Accelerometertb7			
		7	16	17	19
Animal	801	Week3	Week2	Week1	Week4
	811	Week1	Week4	Week3	Week2
	818	Week2	Week1	Week4	Week3
	831	Week4	Week3	Week2	Week1
		Accelerometer			
		14	15	20	22
Animal	907	Week4	Week2	Week1	Week3
	914	Week3	Week1	Week4	Week2
	919	Week2	Week4	Week3	Week1
	950	Week1	Week3	Week2	Week4
		Accelerometer			
		8	10	18	21
Animal	009	Week4	Week1	Week3	Week2
	014	Week2	Week3	Week4	Week1
	017	Week3	Week2	Week1	Week4
	019	Week1	Week4	Week2	Week3

Table 2
Fourteen features and the equation used to calculate predictive metric.

Feature	Equation
Average X-axis (A_x)	$A_x = \frac{1}{T}\sum_1^T(x(t))$
Average Y-axis (A_y)	$A_y = \frac{1}{T}\sum_1^T(y(t))$
Average Z-axis (A_z)	$A_z = \frac{1}{T}\sum_1^T(z(t))$
Average All-Axis (A_{xyz})	$A_{xyz} = \frac{1}{T}\sum_1^T(x(t)+y(t)+z(t))$
Minimum X-axis (Min_x)	The minimum X-axis value in the epoch
Minimum Y-axis (Min_y)	The minimum Y-axis value in the epoch
Minimum Z-axis (Min_z)	The minimum Z-axis value in the epoch
Maximum X-axis (Max_x)	The maximum X-axis value in the epoch
Maximum Y-axis (Max_y)	The maximum Y-axis value in the epoch
Maximum Z-axis (Max_z)	The maximum Z-axis value in the epoch
Standard Deviation X-axis (SD_x) where $\bar{x}$ is the mean of X-axis value in the epoch	$SD_x = \sqrt{\frac{1}{T}\sum_{t=1}^T(x(t)-\bar{x})^2}$
Standard Deviation Y-axis (SD_y) where $\bar{y}$ is the mean of Y-axis value in the epoch	$SD_y = \sqrt{\frac{1}{T}\sum_{t=1}^T(y(t)-\bar{y})^2}$
Standard Deviation Z-axis (SD_z) where $\bar{z}$ is the mean of Z-axis value in the epoch	$SD_z = \sqrt{\frac{1}{T}\sum_{t=1}^T(z(t)-\bar{z})^2}$
Average Standard Deviation all-axis (SD_{xyz})	$VAR_{xyz} = \frac{1}{3*T}*(SD_x^2*T+SD_y^2*T+SD_z^2*T)$ $SD_{xyz} = \sqrt{VAR_{xyz}}$

Table 3
Five calculated metrics utilized as predictive metrics for machine learning behavior predictions.

Feature	Equation
Movement Intensity (MI)	$MI = \frac{1}{T}\sum_{t=1}^T\sqrt{x(t)^2+y(t)^2+z(t)^2}$
Signal Magnitude Area (SMA)	$SMA = \frac{1}{T}\sum_{t=1}^T(\lvert x(t)\rvert+\lvert y(t)\rvert+\lvert z(t)\rvert)$
Energy (Energy)	$Energy = \frac{1}{T}\sum_{t=1}^T(x(t)^2+y(t)^2+z(t)^2)^2$
Entropy (Entropy)	$Entropy = \frac{1}{T}\sum_{t=1}^T(1+(x(t)+y(t)+z(t))^2)*\ln(1+(x(t)+y(t)+z(t))^2)$
Movement Variation (MV)	$MV = \frac{1}{T}\sum_{t=2}^T(\lvert x(t-1)-x(t)\rvert+\lvert y(t-1)-y(t)\rvert+\lvert z(t-1)-z(t)\rvert)$

2.6. Statistical analysis

Mean movement intensity, MV, energy, entropy, SMA, and predicted active behavior were used as dependent values in a 4 × 4 Latin-square design (16 experimental units per Latin square) using PROC MIXED in SAS (SAS Institute Inc., ND, USA; [36]). The dependent variables were averaged by ewe for each week of the study. Fixed effects were week (1 to 4), accelerometer, and ewe. Each Latin-square, an age group (born in 2018, 2019 or 2020) was analyzed separately. Mean separation tests were evaluated using the pdiff feature of PROC MIXED.

Movement intensity, MV, energy, entropy, SMA, and predicted active behavior were used as dependent values were also averaged by hour by ewe and then analyzed using the repeated measures procedure of PROC MIXED in SAS ([22] as a 4×4 Latin-square ($n = 12$). Each Latin-square, based on the ewe year of birth, was analyzed separately. The fixed effects in the model include week (1 to 4), day within week (1 to 5), hour within day (0 to 23), accelerometer, and ewe. The subject of the repeated measures was sheep within week. The covariance of repeated records was modeled using the autoregressive order of 1 (AR1) covariance structure. The AR1 structure has a lower Akaike Information Criterion (AIC) value than the other covariance structures evaluated, compound symmetry and unstructured [22]. Mean separation tests were evaluated using the pdiff feature of PROC MIXED.

3. Results

The initial random forest model utilized the four observed behaviors (laying, standing, feeding, and nibbling) for prediction. Standing was usually predicted as laying and nibbling was predicted as feeding. We merged the four observed behaviors into active (feeding and nibbling) and inactive (laying and standing) to create a binary classification model.

The random forest model had an out-of-bag (OOB) error rate of 6.26 %. The training dataset predicted the 'active' behavior 100 % correctly. The test dataset had prediction accuracy of 95.35 %. The model used approximately 175 of the 300 grown trees. The importance of variables is calculated using the Mean Decrease Accuracy and Mean Decrease Gini. Mean Decrease Gini is the average of a variables total decrease in node impurity, weighted by the proportion of samples reaching that node in each tree within the forest. The order of importance of variables used in the model were MV, Energy, MI, Entropy, and SMA based off Mean Decrease Accuracy (Table 4, Fig. 1). The random forest model prediction had receiving operator characteristics (ROC) area under the curve of 0.961. The random forest model predicted 82.6 % of the observed dataset.

3.1. 2018 ewes

There were differences in weekly MV due to the main effects of accelerometer ($P = 0.0005$), week ($P = 0.0207$), and sheep ($P < 0.0001$) during this study. The greatest differences in means of MV (highest minus lowest) were 0.04037, 0.05191, and 0.02900 for accelerometer, sheep, and week, respectively (Tables 5–7). For the hourly averages, the analysis of repeated measures found detectable differences of hour of the day ($P < 0.0001$) in addition to differences of accelerometer, week and sheep ($P = 0.0029$, $P = 0.0125$, $P = 0.0008$) with no detectable differences for day of the week ($P = 0.17$).

There were differences in the weekly averages for energy due to the main effects of accelerometer ($P < 0.0001$), week ($P = 0.0032$), and sheep ($P < 0.0001$) during this study. The greatest differences in means of energy were 2.7098, 4.0356 and 2.0166 for accelerometer, sheep, and week, respectively (Tables 5–7). For the hourly averages, the repeated measures analysis found detectable differences of day of the week ($P = 0.0317$) and hour of the day ($P < 0.0001$) with no detectable differences of accelerometer, week and sheep ($P > 0.05$).

Table 4
Importance of calculated variables used in random forest machine learning prediction model.

Calculated Metric	Mean Decrease Accuracy	Mean Decrease Gini
Movement Variation	238.55217	490.32945
Energy	46.94281	92.47779
Movement Intensity	28.58495	50.30435
Entropy	23.59104	68.99224
Signal Magnitude Area	20.39243	39.72620

There were differences in MI due to the main effects of accelerometer ($P < 0.0001$), week ($P < 0.0001$), and sheep ($P < 0.0001$) during this study. The greatest differences in means of MI were 0.03298, 0.02475, and 0.02009 for accelerometer, sheep, and week, respectively (Tables 5–7). For the hourly averages, the analysis of repeated measures found detectable differences of hour of the day ($P < 0.0001$) in addition to differences of accelerometer, week and sheep ($P < 0.0001$, $P = 0.0012$, $P = 0.0002$) with no detectable differences due to day ($P = 0.89$).

There were differences in entropy due to the main effects of accelerometer ($P < 0.0001$), week ($P < 0.0001$), and sheep ($P < 0.0001$) during this study. The greatest differences in means of energy were 0.494, 0.6799, and 0.196 for accelerometer, sheep, and week, respectively (Tables 5–7). For the hourly averages, the analysis of repeated measures found detectable differences of day of the week ($P = 0.0013$) and hour of the day ($P < 0.0001$) with no detectable differences of accelerometer, week and sheep ($P > 0.05$).

There were differences in weekly SMA due to the main effects of accelerometer ($P < 0.0001$), week ($P < 0.0001$), and sheep ($P < 0.0001$) during this study. The greatest differences in means of SMA were 0.06392, 0.07873, and 0.05669 for accelerometer, sheep, and week, respectively (Tables 5–7). For the hourly averages, the analysis of repeated measures found detectable differences of day of the week ($P = 0.010$) and hour of the day ($P < 0.0001$) with no detectable differences of accelerometer, week and sheep ($P > 0.05$).

There were differences in weekly activity due to the main effects of accelerometer ($P = 0.0089$) and week ($P < 0.0001$) during this study. No differences between sheep were detected for the 2018 ewes ($P = 0.18$). The greatest differences in means of percent active were 1.056 % and 0.444 % for accelerometer and week, respectively (Tables 5–7). For the hourly averages, the analysis of repeated measures found detectable differences of day of the week ($P < 0.0001$) with no detectable differences of accelerometer, animal, and week ($P > 0.05$).

3.2. 2019 ewes

There were differences in MV due to the main effects of week ($P = 0.0421$), and sheep ($P < 0.0001$) for the 2019 ewes. No differences between accelerometer were detected for the 2019 ewes ($P = 0.09$). The greatest differences in means of MV were 0.08442 and 0.02709 for sheep, and week, respectively (Tables 5–7). For the hourly averages, the analysis of repeated measures found detectable differences of hour of the day ($P < 0.0001$) in addition to differences of accelerometer, week, and sheep ($P = 0.0456$, $P = 0.0269$, $P < 0.0001$) with no detectable differences due to day of the week ($P = 0.13$).

There were differences in energy due to the main effects of week ($P < 0.0001$), and sheep ($P < 0.0001$) in this age group. No differences between accelerometer were detected for the 2019 ewes ($P = 0.24$). The greatest differences in means of energy were 4.5024 and 1.3548 for sheep, and week, respectively (Tables 5–7). For the hourly averages, the analysis of repeated measures found detectable differences of hour of the day ($P < 0.0001$) in addition to differences of, week, and sheep ($P = 0.0145$, $P < 0.0001$) with no detectable differences due to day of the week ($P = 0.19$) or ($P = 0.32$.

There were differences in MI due to the main effects of accelerometer ($P < 0.0001$), week ($P < 0.0001$), and sheep ($P < 0.0001$) for the 2019 ewes. The greatest differences in means of MI were 0.07916, 0.04386, and 0.01952 for accelerometer, sheep, and week, respectively (Tables 5–7). For the hourly averages, the analysis of repeated measures found detectable differences of hour of the day ($P < 0.0001$) in addition to differences of accelerometer, week, and sheep ($P < 0.0001$, $P = 0.0008$, $P < 0.0001$) with no detectable differences due to day of the week ($P = 0.65$).

There were differences in entropy due to the main effects of accelerometer ($P = 0.0124$), week ($P < 0.0001$), and sheep ($P < 0.0001$) during this study. The greatest differences in means of energy were

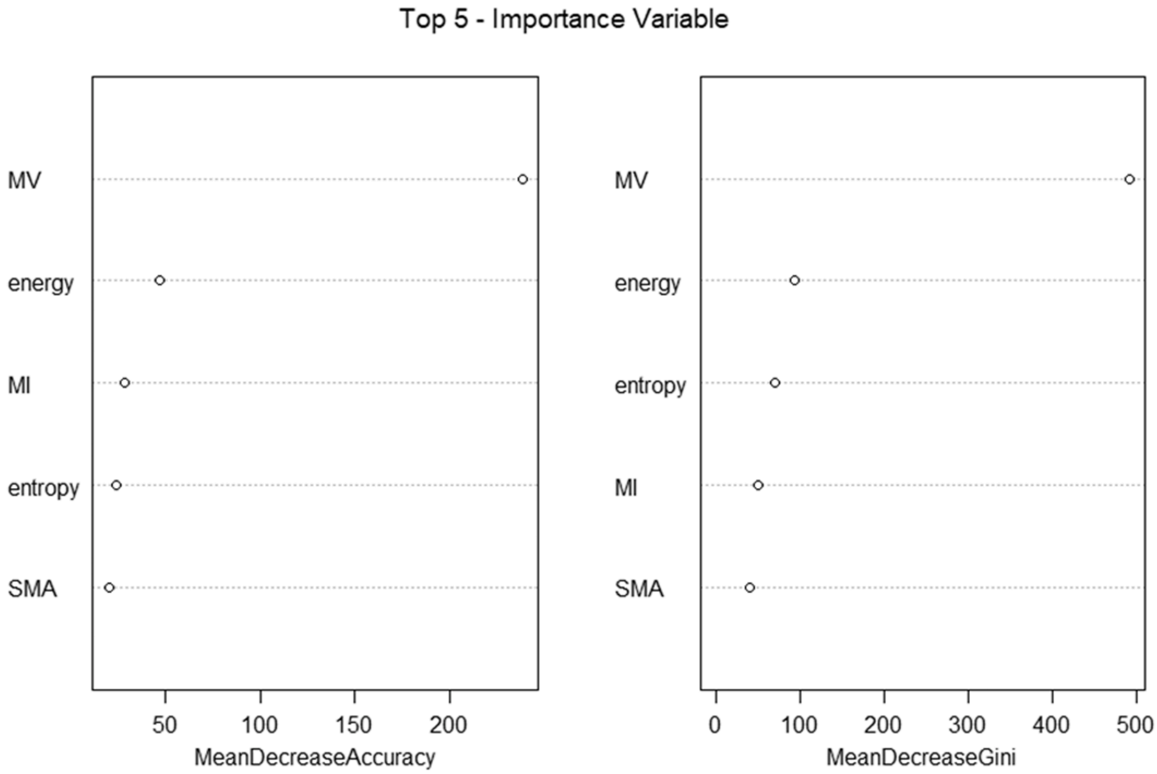

Fig. 1. Mean Decrease Accuracy and Mean Decrease Gini of the five calculated predictor variables, movement variation (MV), energy, movement intensity (MI), entropy and signal magnitude intensity (SMI).

Table 5
Means (±SE) of Movement Variation (MV), Energy, Movement Intensity (MI), Signal Magnitude Area (SMA), Entropy, and Daily Active Percentage for ewes born in 2018–2020 based on analyses that used weekly averages of the dependent variables.

Birth Year	Ewe	MV	SE	Energy	SE	MI	SE	SMA	SE	Entropy	SE	Daily Active,%	SE
2018	801	0.1818	0.004	2.7432	0.399	1.0334	0.002	1.3616	0.029	2.1178	0.032	8.067	0.376
	811	.2000	0.004	6.7788	0.399	1.0086	0.002	1.4114	0.029	1.4379	0.032	8.577	0.376
	818	0.1481	0.004	4.4877	0.399	1.0145	0.002	1.3856	0.029	1.7641	0.032	7.740	0.376
	831	0.1775	0.004	4.1212	0.399	1.0328	0.002	1.3327	0.029	2.0473	0.032	7.898	0.376
2019	907	0.1782	0.005	2.3608	0.288	1.0251	0.002	1.4260	0.005	1.0009	0.043	8.283	0.307
	914	0.2627	0.005	6.8632	0.288	1.0690	0.002	1.3757	0.005	3.1555	0.043	9.026	0.307
	919	0.1858	0.005	3.0535	0.288	1.0298	0.002	1.3474	0.005	1.4802	0.043	8.495	0.307
	950	0.2235	0.005	5.4420	0.288	1.0338	0.002	1.3694	0.005	1.6195	0.043	8.945	0.307
2020	009	0.1625	0.003	5.8243	0.311	1.0074	0.002	1.3469	0.003	2.4497	0.028	8.006	0.282
	014	0.1751	0.003	2.6607	0.311	1.0211	0.002	1.3105	0.003	2.3137	0.028	8.106	0.282
	017	0.1804	0.003	3.6663	0.311	0.9988	0.002	1.2805	0.003	1.9086	0.028	8.649	0.282
	019	0.1573	0.003	2.6015	0.311	0.9968	0.002	1.2704	0.003	1.7577	0.028	7.617	0.282

Table 6
Means (± standard errors, SE) of Movement Variation (MV), Energy, Movement Intensity (MI), Signal Magnitude Area (SMA), Entropy and Activity for accelerometers placed in 2018, 2019 and 2020 age groups based on analyses that used weekly averages of the dependent variables.

Ewe Birth Year	Accelerometer	MV	SE	Energy	SE	MI	SE	SMA	SE	Entropy	SE	Daily Active, %	SE
2018	7	0.1591	0.004	3.4290	0.399	1.0230	0.002	1.3418	0.029	1.7787	0.032	7.600	0.376
	16	0.1995	0.004	6.1388	0.399	1.0384	0.002	1.4012	0.029	1.6314	0.032	8.956	0.376
	17	0.1773	0.004	4.5148	0.399	1.0226	0.002	1.4057	0.029	2.1254	0.032	7.804	0.376
	19	0.1716	0.004	4.0483	0.399	1.0054	0.002	1.3427	0.029	1.8316	0.032	8.750	0.376
2019	14	0.2071	0.005	3.9876	0.288	0.9972	0.002	1.3017	0.005	1.8483	0.043	8.610	0.307
	15	0.2198	0.005	4.3866	0.288	1.0988	0.002	1.4633	0.005	1.7183	0.043	8.685	0.307
	20	0.2004	0.005	4.8233	0.288	1.0196	0.002	1.3644	0.005	1.8294	0.043	8.506	0.307
	22	0.2229	0.005	4.5221	0.288	1.0422	0.002	1.3892	0.005	1.8602	0.043	8.948	0.307
2020	8	0.1695	0.003	3.4610	0.311	1.0464	0.001	1.3608	0.003	2.2942	0.028	7.987	0.282
	10	0.1629	0.003	3.5526	0.311	1.0114	0.001	1.3007	0.003	1.9608	0.028	7.904	0.282
	18	0.1702	0.003	3.9920	0.311	0.9777	0.001	1.2712	0.003	2.0336	0.028	8.257	0.282
	21	0.1726	0.003	3.7471	0.311	0.9887	0.001	1.2755	0.003	2.1411	0.028	8.230	0.282

Table 7
Means (±SE) of Movement Variation (MV), Energy, Movement Intensity (MI), Signal Magnitude Area (SMA), Entropy, and Daily Active Percentage for week 1–4 of the placed in ewes born in 2018–2020 based on Latin-square design analyses that used weekly averages of the dependent variables.

Assigned Ewe Birth Year	Week	MV	SE	Energy	SE	MI	SE	SMA	SE	Entropy	SE	Daily Active, %	SE
2018	1	0.1705	0.004	5.5787	0.399	1.0321	0.002	1.4057	0.029	1.9617	0.032	10.5753	0.376
	2	0.1932	0.004	4.7864	0.399	1.0120	0.002	1.3263	0.029	1.8693	0.032	10.6066	0.376
	3	0.1794	0.004	4.2037	0.399	1.0182	0.002	1.3830	0.029	1.7657	0.032	10.1622	0.376
	4	0.1644	0.004	3.5621	0.399	1.0270	0.002	1.3764	0.029	1.7704	0.032	10.1865	0.376
2019	1	0.2007	0.005	4.0447	0.288	1.0274	0.002	1.3613	0.005	1.5079	0.043	7.6667	0.307
	2	0.2278	0.005	4.7782	0.288	1.0376	0.002	1.4084	0.005	1.7104	0.043	8.6007	0.307
	3	0.2057	0.005	3.4994	0.288	1.0458	0.002	1.3981	0.005	1.8251	0.043	7.8160	0.307
	4	0.2160	0.005	5.3979	0.288	1.0469	0.002	1.3504	0.005	2.2121	0.043	7.9271	0.307
2020	1	0.1693	0.003	4.8184	0.311	1.0019	0.001	1.3184	0.003	2.1174	0.028	7.9549	0.282
	2	0.1893	0.003	4.5014	0.311	1.0064	0.001	1.3024	0.003	2.1089	0.028	7.9167	0.282
	3	0.1575	0.003	2.9650	0.311	1.0032	0.001	1.2829	0.003	1.9969	0.028	8.5382	0.282
	4	0.1591	0.003	2.4679	0.311	1.0127	0.001	1.3048	0.003	2.2065	0.028	8.2500	0.282

Latin square analyses of weekly and hourly averages.

0.1419, 2.1546, and 0.7064 for accelerometer, sheep, and week, respectively (Tables 5–7). For the hourly averages, the analysis of repeated measures found detectable differences of hour of the day ($P < 0.0001$) in addition to differences of week and sheep ($P < 0.0001$, $P < 0.0001$) with no detectable differences due to day of the week ($P = 0.86$) or accelerometer ($P = 0.18$).

There were differences in SMA due to the main effects of accelerometer ($P < 0.0001$), week ($P < 0.0001$), and sheep ($P < 0.0001$) during this study. The greatest differences in means of SMA were 0.1616, 0.07866, and 0.05768 for accelerometer, sheep, and week, respectively (Tables 5–7). For the hourly averages, the analysis of repeated measures found detectable differences of hour of the day ($P < 0.0001$) in addition to differences of accelerometer, week and sheep ($P < 0.0001$, $P = 0.0003$, $P = 0.0002$) with no detectable differences due to day of the week ($P = 0.86$).

There were differences in weekly activity due to the main effects of week ($P < 0.0001$). No differences between sheep or accelerometer were detected for the 2019 ewes ($P > 0.05$). The greatest difference in means for activity were 0.9403 % for week (Tables 5–7). For the hourly averages, the analysis of repeated measures found detectable differences of day of the week ($P < 0.0001$), week ($P = 0.0003$) and animal ($P = 0.0486$) with no detectable differences of accelerometer ($P = 0.46$).

3.3. 2020 ewes

There were differences in MV due to the main effects of week ($P = 0.0014$), and sheep ($P = 0.0375$). No differences between accelerometer were detected for the 2020 ewes ($P = 0.74$). The greatest differences in means of MV were 0.02316 and 0.03174 for sheep, and week, respectively (Tables 5–7). For the hourly averages, the analysis of repeated measures found detectable differences of hour of the day ($P < 0.0001$) in addition to differences of week and sheep ($P = 0.0017$, $P = 0.0081$) with no detectable differences due to day of the week ($P = 0.30$) or accelerometer ($P = 0.29$).

There were differences in energy due to the main effects of week ($P < 0.0001$), and sheep ($P < 0.0001$). No differences between accelerometer were detected for the 2020 ewes ($P = 0.63$). The greatest differences in means of energy were 3.1636 and 2.3505 for sheep, and week, respectively (Tables 5–7). For the hourly averages, the analysis of repeated measures found detectable differences of hour of the day ($P < 0.0001$) in addition to differences of week and sheep ($P = 0.0039$, $P = 0.0009$) with no detectable differences due to day of the week ($P = 0.24$) or accelerometer ($P = 0.64$).

There were differences in MI due to the main effects of accelerometer ($P < 0.0001$), week ($P < 0.0001$), and sheep ($P < 0.0001$) for the weekly means of the 2020 ewes. The greatest differences in means of MI were 0.0686, 0.02431, and 0.01085 for accelerometer, sheep, and week, respectively (Tables 5–7). For the hourly averages, the analysis of repeated measures found detectable differences of hour of the day ($P < 0.0001$) in addition there were differences in accelerometers, weeks and sheep ($P < 0.0001$, $P = 0.0017$, $P < 0.0001$) with no detectable differences due to day of the week ($P = 0.54$).

There were differences in weekly means of entropy due to the main effects of accelerometer ($P < 0.0001$), week ($P < 0.0001$), and sheep ($P < 0.0001$) for the 2020 ewes. The greatest differences in means of entropy were 0.3335, 0.6920, and 0.1205 for accelerometer, sheep, and week, respectively (Tables 5–7). For the hourly averages, the analysis of repeated measures found detectable differences of hour of the day ($P < 0.0001$) and day of the week ($P = 0.0025$) in addition to differences of sheep ($P < 0.0094$) with no detectable differences due to day of the week ($P = 0.59$) or accelerometer ($P = 0.22$).

There were differences in weekly means of SMA due to the main effects of accelerometer ($P < 0.0001$), week ($P < 0.0001$), and sheep ($P < 0.0001$) during this study. The greatest differences in means of SMA were 0.08960, 0.07655, and 0.03522 for accelerometer, sheep, and week, respectively (Tables 5–7). For the hourly averages, the analysis of repeated measures found detectable differences of hour of the day ($P < 0.0001$) in addition to differences of accelerometer, week and sheep ($P < 0.0001$, $P = 0.0021$, $P < 0.0001$) with no detectable differences due to day of the week ($P = 0.15$).

There were differences in weekly activity due to the main effects of animal ($P = 0.0288$) and week ($P < 0.0001$) during this study. No differences between sheep or accelerometer were detected for the 2020 ewes ($P > 0.63$). The greatest differences in means for activity were 1.045 % and 0.6215 % for animal and week, respectively (Tables 5, 6, 7). For the hourly averages, the analysis of repeated measures found detectable differences of day of the week ($P < 0.0001$), week ($P < 0.0001$) and animal ($P = 0.0076$) with no detectable differences of accelerometer ($P = 0.21$).

4. Discussion

Through the random forest machine learning procedure, MV had the greatest Mean Decrease Accuracy. As variables are excluded from the model, the model becomes less accurate. As seen in Fig. 1, MV was the most important variable in terms of accuracy of the model and homogeneity of the nodes within the forest. Movement variation is based on the variation between adjacent epochs (Table 3). and provides an indication of the total amount of variance between epochs to describe the amplitude, frequency, and duration of movement [9]. Prediction of the test dataset had lower accuracy of 82.60 % compared to the overall model of 95.35 %. All active behavior observation misclassifications were during feeding periods. Time of day was not included as a metric during this random forest machine learning procedure. Studies conducted in feedlot settings may be benefited by including time of day.

Although differences in week were detected for almost every analysis, weather during the study were generally mild with few major changes in temperature, wind speed and humidity (Table 7). This study was conducted during typical monsoonal activity. Weeks 1 and 2 both had measurable precipitation while all weeks had varying humidity levels. Average daily temperatures and wind speeds were consistent throughout each week with varying ranges between weeks (Table 4). The effect of week in these analyses are likely a result of changing weather conditions in combination with other undefined factors (Table 8).

Consistently, across the three Latin square experiments using different age groups there were clear differences in MI and SMA among ewes, accelerometers, and weeks with the repeated measures analyses. Differences in ewes and weeks were detected for MV energy and activity from the repeated measures analyses. For the analyses of weekly averages, there were consistent differences among ewes and accelerometers for MI, SMA and entropy. The largest numerical difference among the means of MI was consistent across all age groups for accelerometers, which was surprising because the same model of accelerometer was used throughout the study. Signal magnitude area had larger numerical differences in accelerometer in the 2019 and 2020 age groups while 2018 age group had the largest numerical differences in individual sheep.

Tobin et al. [15] attempted to create a 4-d rolling average to determine the time of the onset of bovine ephemeral fever. The authors identified large contrasts in MI between accelerometers which were used for the study. Accelerometers were exchanged weekly due to limited battery life and MI shifted after each exchange. The shift in MI values when accelerometers caused errors within the moving 4 d rolling averages causing it to change each week, which was an artifact of the differences among accelerometers. These shifts in MI values associated with exchanging accelerometers increased the challenge of detecting the onset of bovine ephemeral fever.

To reduce changes in device weight and changes to inertia in this study, the ear tag was attached using the same ear hole on the ewe and accelerometers were not removed from the tag throughout the study. The attachment of the accelerometer to the Allflex tag was identical for devices. Tolerances among accelerometers sensors during the manufacturing process, though miniscule, could result in minor changes in axis values, resulting in detectable differences among devices.

The observed differences among accelerometers in this study show the importance the experimental design used in behavior studies that use accelerometers. Researchers should set up studies where the statistical model can account for variation among animals and accelerometers, especially if the MI, SMA or entropy metrics are used. If the same accelerometer can be used on an animal for the entire study, cross-over designs and Latin squares can account for the variation in animal and accelerometer device simultaneously. Researchers should avoid changing accelerometers on animals during the study, because this may increase experimental error and decrease precision by amplifying the variation among animals.

For analysis of weekly averages across all age groups, differences in MV were only consistently detected among sheep and week with only the 2018 age group having differences among accelerometers. The largest numerical difference among the means of MV were for sheep and week. When calculating MV, each axis is subtracted from the previous axis reading and the absolute value of each axis is then summed. Movement variation is the only calculated metric evaluated in this study that is based on changes in accelerometer readings rather than the variation of movement readings of each axis. In contrast, MI, SMA, Energy and Entropy directly reflect the numerical values of each reading from each axis. Differences among accelerometer devices for this metrics reflect the recorded values for movements.

Differences among accelerometers can be a confounding factor in experimental designs where accelerometer devices are changed during a study. Differences among accelerometers will likely increase experimental error in designs where devices are not changed because it will likely increase apparent differences among individual animals. In this study, differences among accelerometers were similar in magnitude to differences among individual animals. Variation among animals and accelerometers in some cases could cancel each other out, but this is unlikely. Correspondingly, movement variation may be a better metric than movement intensity, signal magnitude amplitude and entropy.

Aggregating large amounts of datapoints into one mean value can cause information loss [12]. In our analyses, a total of 750, 1080,000 and 7560,000 datapoints were aggregated to create a single metric for minute, day and weekly metric means, respectively. The aggregation of accelerometer data may have diluted the information from the accelerometer. means for the daily active percentage metric. Aggregating data into epochs may be beneficial for herd level analyses but could longer period aggregations such as hourly, daily or weekly may reduce the opportunity to identify behavioral changes within the individual.

This study shows how algorithms developed for individual animals rather than an entire herd may be more useful for detecting behavioral

Table 8
Weather conditions throughout the study, including the maximum, average, and minimum of temperature, humidity, and wind speed, and precipitation.

	Date	Temperature (°C)			Humidity (%)			Wind Speed (m/sec)			Precipitation (mm)
	Aug	Max	Avg	Min	Max	Avg	Min	Max	Avg	Min	Total
Week 1	25	36.44	28.88	20.92	79.28	42.48	20.3	11.70	4.70	0	0
	26	34.91	28.87	21.43	60.38	35.95	20.64	12.42	6.10	0	0
	27	34.61	27.66	21.33	60.82	42.16	20.37	17.96	5.53	0	0
	28	35.04	27.46	20.95	70.23	45.98	22.08	16.45	5.11	0	0
	29	34.58	28.15	20.25	69.39	41.46	20.58	13.35	5.72	0	0
	Sep	Max	Avg	Min	Max	Avg	Min	Max	Avg	Min	Total
Week 2	1	27.57	23.49	20.82	93.00	77.34	56.78	16.23	4.39	0	1.27
	2	33.07	25.73	19.65	94.20	62.93	27.24	10.47	3.42	0	0
	3	34.41	27.09	19.68	83.60	50.85	26.57	17.28	3.90	0	0
	4	34.16	27.02	23.77	70.38	51.59	28.28	16.56	5.61	0	5.58
	5	29.64	25.09	21.97	77.27	59.79	40.88	17.28	3.97	0	0.25
	Sep	Max	Avg	Min	Max	Avg	Min	Max	Avg	Min	Total
Week 3	8	35.05	27.41	18.78	69.75	39.24	18.15	15.40	5.67	0	0
	9	34.38	27.26	19.83	64.62	40.45	19.66	11.95	4.47	0	0
	10	34.58	26.07	17.21	69.77	39.75	13.87	10.08	2.66	0	0
	11	35.28	25.81	16.2	72.20	36.88	10.77	9.72	3.03	0	0
	12	33.75	25.86	16.57	53.19	29.17	14.23	10.83	4.10	0	0
	Sep	Max	Avg	Min	Max	Avg	Min	Max	Avg	Min	Total
Week 4	15	34.28	27.31	21.06	55.15	30.91	19.53	14.54	5.32	0	0.25
	16	35.66	26.95	19.22	58.71	32.79	14.07	9.07	3.29	0	0
	17	35.84	26.25	15.86	67.23	33.36	10.6	9.93	2.78	0	0
	18	35.99	26.64	18.29	56.15	29.02	10.87	10.40	3.87	0	0
	19	35.49	27.42	17.84	59.83	33.23	16.67	11.30	4.58	0	0

changes associated with illness or welfare concerns. Physical characteristic differences lead to high inter-animal variability which results in changing expressions of same behaviors [5]. Splitting datasets by animal can be computationally expensive but may increase overall accuracy. Sprinkle et al. [30] had lower instances of bad data with improved behavior prediction when datasets were analyzed separately by animal rather than the global formula. Chang et al. [10] also found important differences among animals when using accelerometers to predict rumination in cattle. These authors also recommended developing separate detection algorithms for each animal.

However, commercial applications using accelerometers to detect behavior or wellness concerns often use one algorithm rather than different algorithms developed for each individual animal. If a single algorithm must be developed, this study suggests that metrics such as MV would be more useful than MI or SMA. Also, predicted behavior such as activity (%) that is developed data collected from multiple animals and evaluated with machine learning may be more useful than MI or SMA metrics for a single algorithm used for entire herds. In this study, MV was the best predictor of activity using random forests machine learning, which shows the value of MV over metrics such as MI, SMA, Energy and Entropy. Use of predicted behaviors may not always be a better alternative to detect animal wellbeing concerns than monitoring metrics such as MV directly. Gurule et al. [19] found that changes in variation in recorded movements were more successful in predicting lambing than using predicted active or inactive behavior derived from supervised machine learning. Development of predicted behaviors from accelerometer data using supervised machine learning, such as Random Forests, also requires collection of numerous behavior observations, which may not always be practical in extensive settings.

5. Conclusions

Our study has demonstrated the variability that occurs among tri-axial accelerometer and individual animal while monitoring behavior using accelerometers. Differences among accelerometers was often similar in magnitude to differences among individual animals and weekly time periods. When using multiple accelerometers throughout a study, researchers need to account for differences among devices even when sourced from the same manufacturer. Future applications of multiple sensors, including accelerometers, must be carefully monitored to evaluate differences among units, which may diminish trust and further usage of technologies. In addition, the variation among animals and sensor devices should be considered when developing algorithms to detect illness and welfare concerns from remote monitoring. Algorithms based on changes in behavior of individual animals are likely to more accurate than approaches that uses the same values or thresholds for an entire herd. If a single metric must be used for an entire herd or herds, algorithms that monitor changes in accelerometer readings such as movement variation, will likely be more accurate and precise than those calculated directly from movement readings.

Funding

This research was funded by the New Mexico Agricultural Experiment Station, Las Cruces, (NMGifford-A19) from the USDA National Institute of Food and Agriculture and NM (Hatch project NMBailey-15H), North Dakota Agricultural Experiment Station.

Ethics statement

Not applicable: This manuscript does not include human or animal research.

X If this manuscript involves research on animals or humans, it is imperative to disclose all approval details.

CRediT authorship contribution statement

Colin Tobin: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – original draft. **Derek Bailey:** Formal analysis, Funding acquisition, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Caroline Wade:** Data curation, Investigation. **Ly Ly Trieu:** Methodology, Writing – original draft. **Kelsey Nelson:** Data curation, Investigation. **Cory Oltjen:** Data curation, Investigation. **Huiping Cao:** Methodology. **Tran Cao Son:** Methodology. **Victor Flores:** Data curation, Investigation. **Briza Castro:** Data curation, Investigation. **Jennifer Hernandez Gifford:** Funding acquisition, Project administration, Resources. **Mark Trotter:** Methodology, Writing – original draft, Writing – review & editing. **David Kramar:** Methodology, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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