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# Classification of behaviors of free-ranging cattle using accelerometry signatures collected by virtual fence collars

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Precision farming technology, including GPS collars with biologging, has revolutionized remote livestock monitoring in extensive grazing systems. High resolution accelerometry can be used to infer the behavior of an animal. Previous behavioral classification studies using accelerometer data have focused on a few key behaviors and were mostly conducted in controlled situations. Here, we conducted behavioral observations of 38 beef cows (Hereford, Limousine, Charolais, Simmental/NRF/Hereford mix) free-ranging in rugged, forested areas, and fitted with a commercially available virtual fence collar (Nofence) containing a 10Hz tri-axial accelerometer. We used random forest models to calibrate data from the accelerometers on both commonly documented (e.g., feeding, resting, walking) and rarer (e.g., scratching, head butting, self-grooming) behaviors. Our goal was to assess pre-processing decisions including different running mean intervals (smoothing window of 1, 5, or 20 seconds), collar orientation and feature selection (orientation-dependent versus orientation-independent features). We identified the 10 most common behaviors exhibited by the cows. Models based only on orientation-independent features did not perform better than models based on orientation-dependent features, despite variation in how collars were attached (direction and tightness). Using a 20 seconds running mean and orientation-dependent features resulted in the highest model performance (model accuracy: 0.998, precision: 0.991, and recall: 0.989). We also used this model to add 11 rarer behaviors (each < 0.1% of the data; e.g. head butting, throwing head, self-grooming). These rarer behaviors were predicted with less accuracy because they were not observed at all for some individuals, but overall model performance remained high (accuracy, precision, recall >98%). Our study suggests that the accelerometers in the Nofence collars are suitable to identify the most common behaviors of free-ranging cattle. The results of this study could be used in future research for understanding cattle habitat selection in rugged forest ranges, herd dynamics, or responses to stressors such as carnivores, as well as to improve cattle management and welfare.

## KEYWORDS

free-ranging cattle, behavioral classification, animal behavior, accelerometry, virtual fence collars

## 1 Introduction

Livestock grazing, whether in intensive (feed lots and pastures) or extensive (free-range) systems is a traditional practice that has persisted in our modern society to cope with increasing food production demands (Michalk et al., 2019; Komarek et al., 2021). Within this tradition, the ever-expanding development of modern technology has allowed for the growth of precision livestock farming management and research (Eastwood et al., 2017). Indeed, this management approach focuses on the fine-scale monitoring of individuals' health and food intake (Schellberg et al., 2008; Werkheiser, 2018). While it remains relatively easy to implement in barn and pasture settings, free-range farming presents additional challenges; herd supervision can become more difficult as cattle are not contained. Additionally, external factors affecting cattle such as exposure to climatic extremes, parasitic load, untreated diseases, accidents, and potential carnivore effects are complex to monitor (Hutchings et al., 2000; Silanikove, 2000; Sevi et al., 2009; Nedeva, 2020). Technological advances such as biosensors, camera-equipped drones and GPS collars have offered scientists, managers and farmers tools to address those challenges (Herlin et al., 2021).

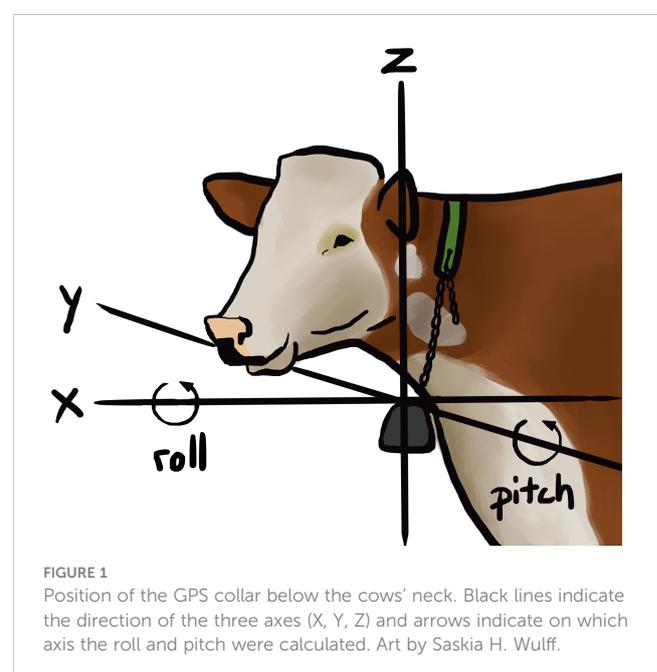
Notably, modern GPS collars, which often contain accelerometry sensors, provide researchers with an opportunity for non-invasive, low maintenance and remote monitoring of livestock and wildlife. If properly calibrated, this allows for the study of fine-scale animal behavior, activity budgets and energy expenditure on an individual level (Vázquez Diosdado et al., 2015; O'Leary et al., 2020; Mulvenna et al., 2022). Even though accelerometry data has largely increased our understanding and knowledge of livestock behavior (Theurer et al., 2013; Uenishi et al., 2021), most behavioral studies using accelerometry sensors focus on a few key behaviors such as grazing, resting, and walking (Robért et al., 2011; Homburger et al., 2014; Benaissa et al., 2019), and they are conducted in controlled settings such as barns and pastures (Homburger et al., 2014; Hendriks et al., 2020; Rodriguez-Baena et al., 2020).

Very few studies examine the behavior of free-ranging cattle in remote areas, where cattle are difficult to monitor and observe due to them moving over large areas and using dense vegetation types (Tofastrud et al., 2019). Yet, in these conditions, behaviors such as vigilance, social behaviors or grooming can be representative of stress, as cows have been reported to increase vigilance when stressed (Welp et al., 2004), and to decrease milk production when separated from the herd and not allowed to perform social behaviors (Hedlund and Løvlie, 2015). In addition, self and allogrooming are reported to be frequent as maintenance behaviors and shown to be an important proxy for welfare (Kohari et al., 2007). While these behaviors are important to monitor, they are especially difficult to observe. Tofastrud et al. (2018) used two-axial accelerometry data at five-minute intervals on free-ranging cattle to study resting, grazing and movement activity patterns. Although this allows for insight into general free-ranging cattle behavioral habits in remote areas, it lacks the ability to precisely quantify additional, rarer behaviors and restricts the amount of information capable of being calibrated and further studied. Continuous, high resolution (10Hz) tri-axial accelerometry data can potentially increase the number of behaviors that can be

classified and provide more detailed information about cattle behavior in large rugged, forested ranges (Hounslow et al., 2019). Such studies could contribute to the improvement of farmer monitoring systems related to high precision farming in outfields and offer the possibility to study effects from external factors, such as carnivores, on cattle behavior while monitoring welfare.

There are numerous ways to analyze accelerometry data, ranging from simple decision trees to complex neural networks (Riaboff et al., 2022). Most studies utilize supervised machine learning methods such as random forest (de Weerd et al., 2015; Williams et al., 2020; Riaboff et al., 2022), while others use unsupervised machine learning such as hidden Markov Models (Leos-Barajas et al., 2017; Chimienti et al., 2021; Rautiainen et al., 2022). Supervised methods provide the advantage of allowing for accelerometry data to be calibrated on actual behavioral observations, which then allows for prediction of behaviors based on collected data.

Feature selection is the first step in this process. Features can be calculated and extracted from raw accelerometry data and be used for behavioral classification. Orientation dependent features, such as the mean and variance of the raw  $x$ ,  $y$ ,  $z$  values, body pitch roll, yaw and dynamic acceleration (Figure 1) remain sensitive to the sensor's orientation (Abell et al., 2017; Benaissa et al., 2019). For example, even though collars are assumed to be stationary positioned on the animal, there can be noise related to rotation, collar deployment errors, and other causes. This may result in additional variability in orientation-dependent features, which may render these features unusable without correcting for orientation (Williams et al., 2017; Barker et al., 2018; Kamminga et al., 2018). This sensitivity can be challenging when standardizing accelerometer sensor placement during animal handling, and recapturing individuals to manually fix issues is difficult (Chakravarty et al., 2019; Cade et al., 2021; Rautiainen et al., 2022). To remedy this problem, orientation independent features can be utilized. Models can then account for



displacement of the sensor's orientation and make obsolete the need to correct for orientation.

High resolution (> 1Hz) accelerometry data is usually smoothed with a running average over a given time window (Shepard et al., 2008a). The chosen window length can result in the loss of certain less frequent and shorter behaviors that might not be detectable, while longer lasting, more common behaviors increase the accuracy and precision of the predictions (Mansbridge et al., 2018; Chang et al., 2022). Therefore, clear study goals become essential in accelerometry analysis, as the study aim will determine different trade-offs and decisions for modeling (Chang et al., 2022).

For instance, some authors suggest that averaging values in the sensor provides an opportunity to increase data collection capacity, and thus allows for live monitoring of behaviors with computationally simple and cost-efficient features and algorithms, which reduce battery usage (Kamminga, 2020; Nuijten et al., 2020). Study questions will thus determine data collection methods, which resolution the data needs to be collected in, as well as which steps should be included in the pre-processing. This will induce trade-offs which will determine what type and number of behaviors that can be analyzed (Kamminga et al., 2018; Riaboff et al., 2022).

In this paper, we aim to calibrate high-resolution accelerometry data collected by commercially available livestock collars deployed on free-ranging cattle in remote areas. Additionally, we aim to investigate the effect of collar placement during deployment of collar and how it might affect accelerometry data. Finally, we attempt to address the gap in knowledge concerning the classification of less frequent cattle behaviors to accelerometry data, as these behaviors can represent behavioral changes or even be indicators of stress.

Our classification study contributes to potential research on cattle social interactions, behavioral responses to carnivores, and energy expenditure of free-ranging cattle in remote forested areas. Additionally, this study has the potential to develop tools for improved monitoring systems for farmers, and therefore to contribute to the practice of agroforestry and precision livestock farming.

We first hypothesized that the model performance to predict general behaviors such as walking (locomotion), foraging, vigilance, standing, laying/resting, or ruminating, would be affected by the choice of features included in the models (orientation-dependent versus orientation-independent features) and by the direction of the collar position on the neck of the animals (as we wanted to account for collar placement variation by the farmers on cattle) (H1). Models with orientation-independent features might perform better than those using orientation-dependent features, as orientation-independent features can account for potential rotation or tightness differences of collars when individuals navigate through rugged terrain. Additionally, models including orientation-dependent features corrected for direction might perform better than those without correction.

Secondly, we hypothesized that less frequent behaviors such as social interactions and body care movements would be impacted by the smoothing of the data (H2). Data smoothed with a short running mean would allow for the detection of rarer behaviors,

but at the cost of a loss in the overall model's performance as a short running window mean can induce more noise during the analysis.

## 2 Methods

### 2.1 Study area

We collected data in three summer grazing ranges in the Innlandet county of Norway. This region of Norway belongs to the boreal forest biome and is dominated by coniferous forest, mires and lakes, and only about 4% is covered by agricultural fields. Many beef cattle breeders release their suckler cows with their calves into the forest during the summer months, to make use of outfield grazing resources and to spare the fields close to the farm for winter forage production. The summer ranges included in this study (Steinvik 27.2 km<sup>2</sup>, long = 11.28°, lat = 61.23°, Deset west 16.4 km<sup>2</sup>, long = 11.42°, lat = 61.29°, Tørberget 5.8 km<sup>2</sup>, long = 12.29°, lat = 61.08°) consisted of a patchwork of forest stands of different age classes due to clearcutting practices, often followed by soil scarification, thinning and other silvicultural practices used to increase timber production. Forest stands were either dominated by Norway spruce (*Picea abies*) or Scots pine (*Pinus silvestris*), interspersed with birch (*Betula pendula*, *B. pubescens*) and other deciduous species. Only minor parts of the ranges were covered by bogs and old grazing meadows. The terrain was rugged and covered an elevational gradient of 300 – 640 m above sea level. A network of forest roads connected the forest stands. Earlier studies in similar habitat have shown that cattle prefer to graze in young forest stands (Tofastrud et al., 2019), where there is access to graminoids of different species (Spedener et al., 2019). However, clearcutting and soil scarification induced varied landscapes that force wildlife and free-ranging livestock to walk on uneven, rugged terrain with obstacles such as fallen trees, stumps, and tree residuals after logging.

### 2.2 Study animals

All suckler cows belonging to four farms were fitted with virtual fence collars (Nofence, 2022) in May 2021. The farmers trained the cows for virtual fencing while still at the farm, following the instructions given by Nofence (Nofence, 2022). In end of May and beginning of June, the cows were released into their summer grazing ranges (45 cows Steinvik, 21 cows in Deset West, and 13 cows in Tørberget), along with their (uncollared) calves. The grazing ranges were delimited by virtual fencing, and range size did not change much during the summer season. In this study, we included data from 38 cows (4 – 16 individuals per farm) of the following breeds: Hereford (n = 16), Limousine (n = 5), Charolais (n = 4), and 13 crossbred individuals including the beef breeds Simmental, Hereford and the dual-purpose breed Norwegian Red (NRF) (Supplementary Table 1).

Nofence collars with virtual fencing technology (Brunberg et al., 2017; Werkheiser, 2018; Søraa and Vik, 2021; Verdon et al., 2021) triangulate the positions of animals (1 position every 5 to 15

minutes) through the GNSS (Global Navigation Satellite Systems), as well as record movement activity with a motion sensor that yields high-resolution tri-axial accelerometry data (10Hz). The battery is designed to last for at least three months and to be continuously recharged through solar panels. Each animal carried a total weight of 1446g. As cows weighted between 500 and 900 kg depending on the breed and age, collars made up about 0.3-0.5% of the body weight. These devices fell under the recommended threshold of 3-5% of an animal's body mass (Arnemo et al., 2011; Soulsbury et al., 2020; Hamidi et al., 2022; Sonne et al., 2022).

### 2.3 Accelerometry sensor activation

Accelerometry sensors on the Nofence collars were remotely activated to continuously sample and transmit data during bouts of 48h. Bouts were distributed throughout the grazing season at intervals of minimum three weeks between bouts per cow, to enable the solar-powered batteries to recharge. This resulted in 1-5 sampling bouts per monitored cow. The order of activation followed a somewhat opportunistic design, depending on where the cows were in relation to each other and in relation to the habitat type. Cows in dense forest were difficult to observe, and we therefore activated mostly collars of cows in more open habitat types.

### 2.4 Video data

A team of two people located and filmed adult individual cattle in-field while the collars' accelerometers were activated (Arablouei et al., 2021). To ensure a maximum number of behaviors was captured, we filmed the cattle throughout the summer, in varying weather conditions, times of day, and terrains. The team located the cattle with the Nofence app (Nofence, 2022), which displays the latest positions of individuals.

Carrying a video camera (Canon XA40, Canon Inc.), the team approached the herds as quietly as possible (min. 10 - 15 m distance) to minimize disturbance and stress. When the habitat was open (e.g., clearcuts), the team filmed the entire herd, but when the vegetation was dense, the team focused on filming single individuals. Individual cows were identified by their earmarks and color patterns, using direct observation, binoculars or camera zoom. Video clips lasted between 24 seconds to 48 minutes and were downloaded from the internal memory card every evening, to be stored on a One Drive folder for later use.

All video footage was then viewed and tagged in the software BORIS (Friard and Gamba, 2016), an open-source platform for behavioral coding of video/audio files, to identify and label individual cattle behavior (done multiple times for the same video if multiple individuals in the footage). This was done using an ethogram with a total of 42 behaviors and postures in the following categories: alert, body care, excretion, intake, locomotion, posture, posture transition and social interaction. This ethogram was constructed to be as inclusive as possible of all cattle behaviors (Langford et al., 2011; MacKay et al., 2013; Petherick et al., 2013; Tofastrud et al., 2018; Navarro et al., 2019) and was further detailed

with field observations (Supplementary Table 2). The principal investigator of the fieldwork and video analysis labeled ~95% of the video material and trained and supervised three students for the remaining videos, thus minimizing observer bias.

### 2.5 Pre-processing of the accelerometry data

The software R, version 4.2.1 (R Core Team, 2022) with the Rstudio interface (R Studio Team, 2021) was used for data pre-processing, analysis, and visualization. The tri-axial accelerometry data was matched with the corresponding video data. First, the approximate time stamps of the tri-axial accelerometry data were calculated in decimal seconds. Raw data files have rounded timestamps, up to 32 observations per timestamp, while the data was collected at 10Hz. We converted this to unique timestamps with decimal seconds by subtracting the amount of time that had passed since the last rounded timestamp (i.e., when the time stamp was 13:02:02, and it was the 5th observation, we subtracted 2.7 seconds  $((32-5)/10)$  from the original time stamp). Double observations were then removed, resulting in a data set of approximately 10Hz with an error of  $\pm 0.5$  seconds. Due to this rounding error, possible time drift in video recordings, and to reduce observer bias in video analysis, we excluded any behavior which had a shorter length than five seconds.

In the next step, the behavioral data was matched with the accelerometry data by timestamp using the function 'foverlaps' from the *Data.table* package (Dowle and Srinivasan, 2019). For the initial match, all behaviors were used (Supplementary Table 2). However, as some behaviors overlapped with each other and we could only keep one single behavior per observation for the analyses, we introduced decision rules based on cattle ecology and body movement (Supplementary Figure 1, Supplementary Table 3). For example, grazing behavior was prioritized over walking, and vigilant behavior was considered only when no other behaviors were shown, to avoid noise in the accelerometry signature from the other behaviors. Behaviors that made up less than 1% of all observation time were pooled into one class named 'other'.

### 2.6 Features calculation

We used the raw accelerometry data to calculate orientation dependent and independent features to avoid additional complex pre-processing steps and to reduce the need for computing power. The mean and the standard deviation were calculated along the three axes (Table 1) using 1, 5, and 20 seconds running means, following previous work with accelerometry data on cattle (Riaboff et al., 2022). The pitch is the angle of the collar in degrees ( $^{\circ}$ ) along the x axis (Figure 1, Equation 1) where the collar is facing upwards for a  $+90^{\circ}$  angle and downwards for a  $-90^{\circ}$  angle. Similarly, the roll is the angle of the collar along the y axis (Figure 1, Equation 2) (Shepard et al., 2008b; Chimienti et al., 2016). Thereafter, we calculated the mean and standard deviation of the pitch and roll across the three-running means (Table 1).

**TABLE 1** Overview of the features used in the models: orientation dependent (three axis, body pitch, and body) and orientation independent (overall dynamic body acceleration (ODBA), vector of dynamic body acceleration (VEDBA), and magnitude of acceleration (AMAG)).

Orientation	Features	Definition
Dependent	Mean X, Y, Z	Mean acceleration recorded from the accelerometer (g) across the running mean for all three axis (X,Y,Z)
	Standard deviation X, Y, Z	Standard deviation of the acceleration recorded from the accelerometer (g) across the running mean for all three axis (X,Y,Z)
	Mean body pitch	Mean angle of the collar along the x axis (degrees) across the running mean.
	Standard deviation body pitch	Standard deviation of the angle of the collar along the x axis (degrees) across the running mean
	Mean body roll	Mean angle of the collar along the y axis (degrees) across the running mean.
	Standard deviation body roll	Standard deviation of the angle of the collar along the y axis (degrees) across the running mean
Independent	Mean ODBA	Overall Dynamic Body Acceleration – Measure of general effort across three axis averaged across the running mean
	Standard deviation ODBA	Standard deviation of the ODBA across the running mean
	Mean VEDBA	Vector of Dynamic Body Acceleration - Vector of the general effort across three axis averaged across the running mean
	Standard deviation VEDBA	Standard deviation of the VEDBA across the running mean
	Mean AMAG	Magnitude of acceleration - Measure of the magnitude of effort across three axis averaged across the running mean
	Standard deviation AMAG	Standard deviation of the AMAG across the running mean

$$Pitch = \arctan\left(\frac{x}{\sqrt{y^2 + z^2}}\right) \tag{1}$$

$$Roll = \arctan\left(\frac{y}{\sqrt{x^2 + z^2}}\right) \tag{2}$$

For the overall dynamic body acceleration (ODBA) and the vector of dynamic body acceleration (VEDBA) we first subtracted the mean acceleration from the raw acceleration for each axis to calculate the dynamic acceleration (respectively noted  $dx$ ,  $dy$ ,  $dz$  for each axis). The sum of the absolute values from the dynamic acceleration was then used to calculate the ODBA (Equation 3), and subsequently the mean and standard deviation of ODBA across the running means (Table 1). The VEDBA was calculated by taking the square root of the squared dynamic acceleration for the three axes (Equation 4), again followed by calculation of mean and standard deviation across the running mean (Table 1). Finally, the magnitude of acceleration (AMAG) was calculated by taking the square root of the squared acceleration for the three axes (Equation 5), with mean and standard deviation across the running mean (Table 1).

$$ODBA = |dx| + |dy| + |dz| \tag{3}$$

$$VEDBA = \sqrt{dx^2 + dy^2 + dz^2} \tag{4}$$

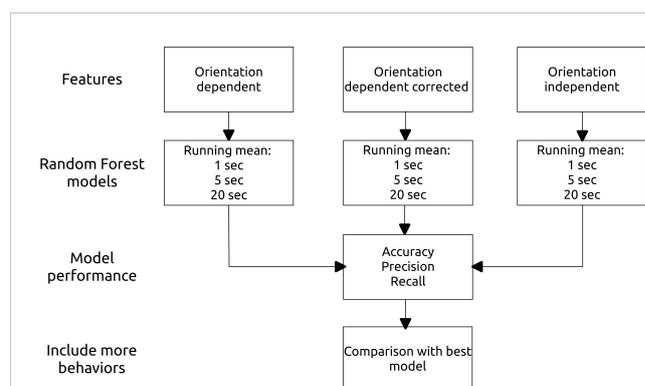
$$AMAG = \sqrt{x^2 + y^2 + z^2} \tag{5}$$

During the analyses, we noticed that about half of the collars were placed in the reverse direction on the cow. We identified these based on the pitch angle from “foraging\_low” behavior (a positive angle suggests a reversed collar), and by looking at the video data (the collars have a small mark to distinguish between left and right

side). The data was then corrected by reversing both x and y axis. The orientation-dependent features were calculated for both the original and the corrected data sets (Figure 2).

### 2.7 Random forest models

We prepared data for orientation-dependent, orientation-dependent with correction, and orientation-independent features (Figure 2). Within each category, we ran three models on the three different running means (1, 5, and 20 seconds). All features were standardized before running the models. The data were grouped by behavior and split with 80% used for training and 20% for validation. Thereafter, random forest models were run using the function ‘*h2o.randomforest*’ from the *H2O* package version 3.36.1.2



**FIGURE 2** Flow chart showing the modeling process. For each feature category (orientation dependent, orientation dependent corrected, orientation independent), we ran three models, one for each running mean (1, 5, and 20 seconds). Furthermore, after assessing the models performance we reran the best model including more behaviors.

(LeDell et al., 2021). We chose the random forest algorithm for its versatility, and because it has good predictive power for its computation time (Biau & Scornet, 2016). Models were run with 150 trees, as with this number of trees, the log-loss of the model became stable. We used 5-fold cross-validation, and we added a weight to each class ( $N$  of rarest behavior divided by the  $N$  of the behavioral class) to account for class imbalance and potential overfitting (Cutler et al., 2012). Additionally, we checked for individual variation by running an individual-based cross-validation (without data split by behavior). The package's default settings were used for the other hyperparameters (max tree depth = 20, mtries = square root of the number of features). We visualized model results using the *DALEX* package (Biecek, 2018) and the *ggplot2* package (Wickham, 2016). Furthermore, the model accuracy, precision, and recall were calculated to compare model performance (Equations 6, 7, and 8, respectively) (Kamminga, 2020). Based on the best performing model, we ran the last model including more behaviors to test if models including more behaviors performed similarly well (Figure 2). Here, the threshold for a behavior to be included was minimum 0.1% of the total observation time.

$$\text{Accuracy} = \frac{n \text{ true positives} + n \text{ true negatives}}{n \text{ positives} + n \text{ negatives}} \quad (6)$$

$$\text{Precision} = \frac{n \text{ true positives}}{n \text{ positives}} \quad (7)$$

$$\text{Recall} = \frac{n \text{ true positives}}{n \text{ true positives} + n \text{ false negatives}} \quad (8)$$

### 3 Results

We annotated 6 898 behavioral observations based on video analysis and matched them with accelerometry data, resulting in a total of 1 240 588 observations for 31 behaviors (Supplementary Table 2). Visual inspection showed appropriate matching, i.e. the accelerometry data showed different signatures for different behaviors (Figure 3).

Overall, the models with 20 seconds running mean performed better than those with shorter running means (Table 2). Orientation-independent models showed a lower performance than orientation-dependent models. Corrected orientation-dependent models performed similar to uncorrected models (Table 2). Both orientation-dependent models with 20 seconds running mean (models C and F) had average accuracy, precision and recall > 0.96. The orientation-independent model I had an average precision of 0.88, recall 0.93 and accuracy 0.99 (Table 2). Precision averaged 0.62 and 0.63 for the 1 second running mean in the orientation-dependent and corrected orientation-dependent models, respectively (models A and D, Table 2), and averaged 0.37 and 0.64 for the 1 second and the 5 seconds running means, respectively in the models with orientation-independent features

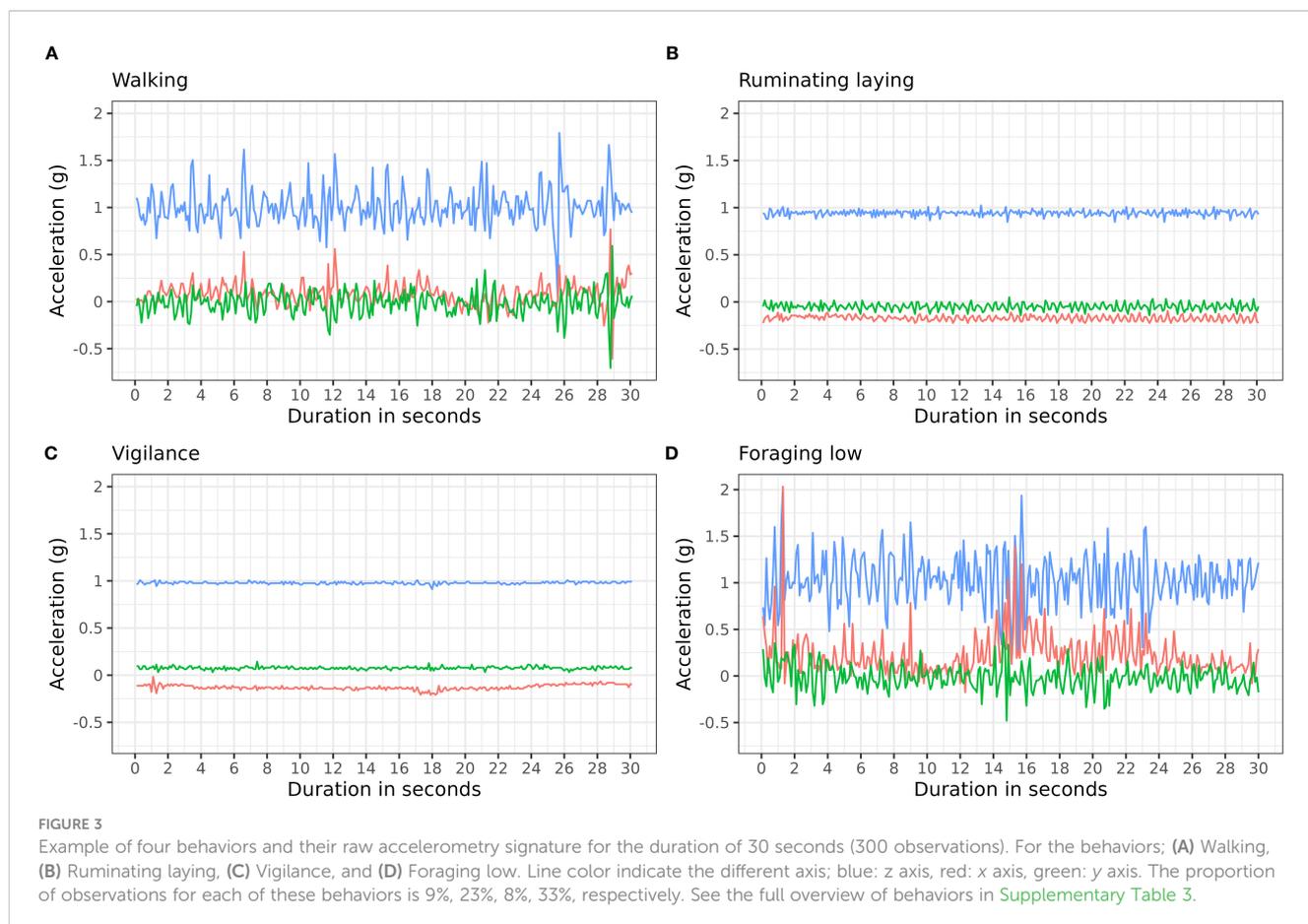


TABLE 2 Overview of the nine models with the average and range for accuracy (as the ratio of correct predictions out of all predictions), precision (as the ratio of true positives over the sum of false positives and true negatives), and recall (as the ratio of correct predicted outcomes to all predictions).

Model	Accuracy	Precision	Recall
(A) Orientation dependent (1 sec)	0.954 (0.907-0.989)	0.617 (0.325-0.894)	0.687 (0.473-0.842)
(B) Orientation dependent (5 sec)	0.985 (0.961-0.997)	0.854 (0.645-0.972)	0.923 (0.839-0.982)
(C) Orientation dependent (20 sec)	0.997 (0.991-0.999)	0.961 (0.875-0.995)	0.985 (0.965-0.999)
(D) Orientation dependent corrected (1 sec)	0.957 (0.908-0.990)	0.629 (0.337-0.898)	0.693 (0.480-0.848)
(E) Orientation dependent corrected (5 sec)	0.986 (0.959-0.998)	0.868 (0.648-0.975)	0.922 (0.826-0.978)
(F) Orientation dependent corrected (20 sec)	0.997 (0.990-1.000)	0.964 (0.872-0.995)	0.985 (0.953-0.999)
(G) Orientation independent (1 sec)	0.918 (0.834-0.974)	0.371 (0.108-0.755)	0.392 (0.080-0.741)
(H) Orientation independent (5 sec)	0.956 (0.901-0.985)	0.642 (0.437-0.881)	0.721 (0.498-0.849)
(I) Orientation independent (20 sec)	0.988 (0.970-0.997)	0.884 (0.798-0.973)	0.931 (0.891-0.981)

(models G and H, Table 2). Similarly, the recall averaged 0.69 for the 1 second running mean in the orientation-dependent and corrected orientation-dependent models (models A and D, Table 2). The orientation-independent models G and H had an average recall of 0.39 and 0.72 for 1 and 5 seconds running mean, respectively (Table 2). Prediction performance varied across behaviors for recall, accuracy and precision (Figure 4, and Supplementary Figures 2, 3, respectively). Behaviors in models with a shorter running mean varied more in recall than in models with a longer running mean, e.g., 'foraging\_high' and 'other' in the orientation-dependent models A and D were below 0.4 (Figure 4). Those behaviors were correctly classified in less than 40% of their occurrence. Orientation-dependent models using 5 seconds running means performed better with lowest recall of 0.8 (model B, Figure 4). For models with 20 seconds running mean, the recall was never below 0.96, showing that the lowest performing behavior had a classification success of 0.96. The performance of the orientation-independent models showed overall lower recall values for each behavior. Still, increased running means in the orientation-independent models helped to improve prediction and decreased the number of classification errors.

The orientation-dependent model with 20 seconds running mean had a few occasions where behaviors were misclassified (Table 3). However, the confusion matrix for the orientation-independent model with 20 seconds running mean showed a higher degree of misclassification (Table 4), especially for behaviors that were more similar in their acceleration signature (e.g. 'foraging\_low' and 'walking', or 'ruminating\_standing' and 'ruminating\_laying'). The confusion matrices for all other models are presented in Supplementary Tables 4–10.

The individual-based cross validation model using a 20 second running mean and orientation-dependent data indicated that rarer behaviors were more difficult to predict for individuals with less observations, but overall, the model performed similar to the model using the 80-20 data split, because there were enough observations of these rare behaviors across all individuals. The averaged accuracy was 0.997, the averaged precision was 0.965, and the averaged recall was 0.987 (See Supplementary Table 11 for the confusion matrix).

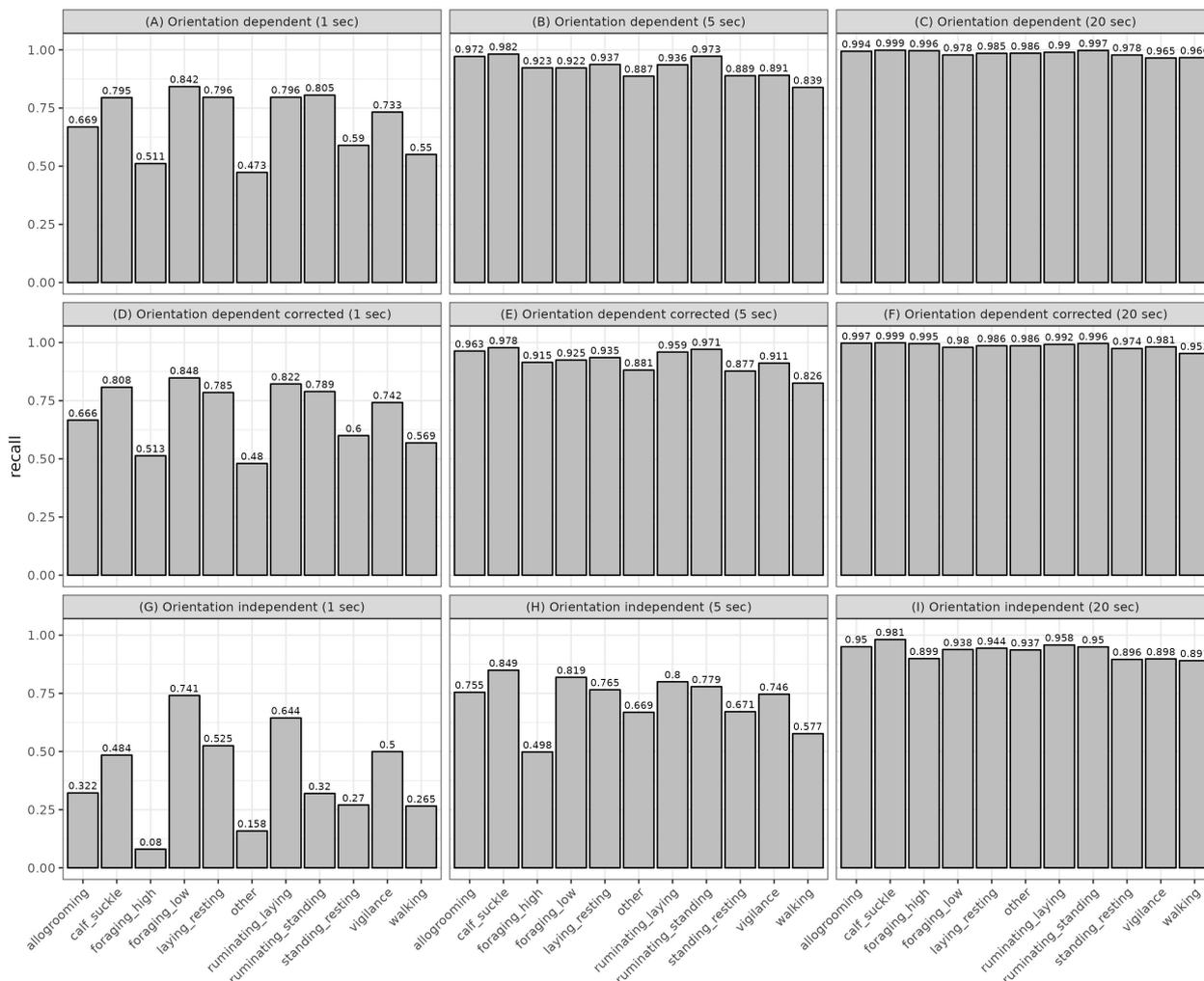
The model including more behaviors had an average accuracy of 0.99, precision of 0.71, and recall of 0.96. The classification success for the behaviors that were also present in the other models performed similarly well (Tables 3–5). However, rarer behaviors had a high classification success with almost no misclassifications, e.g., in the behaviors 'stretching' and 'throw\_head' (Table 5).

## 4 Discussion

In this study, tri-axial accelerometer signatures were assigned to observed behaviors of free-ranging cattle based on supervised machine learning algorithms and using different accelerometer features and running mean smoothing windows. We found that (1) using a long running mean (20 seconds) translated to best model performance across all model categories, and (2) model performance remained excellent when using orientation-dependent instead of orientation-independent features, or when adding more behaviors (with accurate classification even with minority class behaviors i.e., allogrooming, suckling calf).

How tight and in which direction collars were deployed, and terrain ruggedness through which the cows navigated, varied widely in our study. We therefore expected that orientation-independent features derived from accelerometer data, would lead to better prediction performance than orientation-dependent features (hypothesis H1). However, models based solely on orientation-dependent features performed better than those based on orientation-independent features.

While our study assessed the outcome and performance of either orientation-dependent or -independent features, previous studies have combined up to 60 features of both types to increase model performance (Lush et al., 2018; Riaboff et al., 2020; Riaboff et al., 2022). However, as our best model with solely orientation-dependent features had excellent performance (0.997 accuracy, 0.961 precision, 0.985 recall), we did not need to extend the model by including additional orientation-dependent and -independent features. We believe our model performed so well in part because the accelerometer was placed along with the battery and other collar



**FIGURE 4**  
The recall (classification success) for each model, specified by behavior and based on the model's validation data. Rows indicate orientation-dependent features, corrected orientation-dependent features, and orientation-independent features, respectively.

electronics on the low side of the collar. The combined weight of the unit seems to hold the accelerometer in place, independently from collar tightness. In comparable studies on marine mammals, accelerometer placement is highly variable (Shepard et al., 2008b).

Moreover, and contrary to our predictions, we found that correcting for collar orientation did not improve the model performance. Indeed, both corrected and uncorrected models performed similarly. While placing the accelerometer backwards can impact axes values, the accelerometer unit remains below the neck of the animal and hangs similarly for all individuals. In fact, backwards placement of the accelerometer affects only the mean of the X and Y axes, with a more pronounced effect for the X axis, as well as the mean pitch values; the variance of the Z axis and the pitch are not affected by orientation (Wang et al., 2015; Chang et al., 2022). Despite variations in feature values, the amplitude and pattern of movement remain consistent, which might explain why orientation-corrected models did not outperform uncorrected models. Additionally, the sample size in our study is large enough to rule out noise in the data due to collar deployment error, making our models robust (Riaboff et al., 2022).

Furthermore, cattle are large and slow animals, and behavior-specific body movements can be more easily differentiated compared to small-sized animals. This might be more challenging for smaller, faster moving species, and placement of accelerometers in those species, and placement of accelerometers in those species is likely more important (Grünewälder et al., 2012; Brewster et al., 2018).

We initially hypothesized that the detection of less frequent behaviors, such as social interactions and body care movements, would be impacted by the smoothing of the data, as these behaviors might not be detected by long running mean windows. Contrary to our predictions, we found an increase in model performance across all categories (orientation-dependent, orientation-dependent with correction, orientation-independent) with increasing smoothing window, with highest performance when using a 20 second running mean. Other studies have shown that smoothing of the data increases the classification success by reducing noise, and that larger animals often require a longer running mean as their movements are generally slower (Shepard et al., 2008a). However, this often results in a decrease in classification success for behaviors which are rare and short in time

TABLE 3 Confusion matrix for the orientation dependent features without collar correction with 20 seconds running mean.

		Predicted behaviors										
		allogrooming	calf_suckle	foraging_high	foraging_low	laying_resting	other	ruminating_laying	ruminating_standing	standing_resting	vigilance	walking
Actual behaviors	allogrooming	<b>3564</b>	0	4	0	0	0	6	2	9	0	0
	calf_suckle	0	<b>4151</b>	1	0	0	0	4	1	0	0	0
	foraging_high	1	3	<b>7444</b>	10	2	1	0	3	5	1	2
	foraging_low	59	26	815	<b>80698</b>	20	92	21	26	297	74	364
	laying_resting	14	3	6	8	<b>21485</b>	40	150	13	40	46	3
	other	11	1	6	7	3	<b>6446</b>	12	11	21	7	14
	ruminating_laying	30	17	21	6	67	156	<b>56607</b>	152	68	48	17
	ruminating_standing	2	0	0	0	0	0	5	<b>5537</b>	4	0	3
	standing_resting	52	7	44	48	1	103	22	32	<b>17892</b>	31	61
	vigilance	10	70	40	44	17	58	71	96	197	<b>18069</b>	45
walking	12	6	123	340	3	57	24	20	129	20	<b>21166</b>	

Columns represent the predicted behaviors; rows represent the actual observed behavior the validation data set.  
Bold values are the number of observations correctly predicted by the model.

TABLE 4 Confusion matrix for the orientation independent features without collar correction with 20 seconds running mean.

		Predicted behaviors										
		allogrooming	calf_suckle	foraging_high	foraging_low	laying_resting	other	ruminating_laying	ruminating_standing	standing_resting	vigilance	walking
Actual behaviors	allogrooming	<b>3407</b>	2	13	38	7	14	18	3	44	4	35
	calf_suckle	1	<b>4079</b>	1	1	8	2	25	14	14	9	3
	foraging_high	30	13	<b>6721</b>	427	10	14	22	6	70	6	153
	foraging_low	308	113	1120	<b>77405</b>	64	312	143	68	516	126	2317
	laying_resting	3	67	36	21	<b>20589</b>	58	436	92	229	237	40
	other	21	9	21	78	38	<b>6124</b>	47	31	88	10	72
	ruminating_laying	69	267	23	5	493	262	<b>54773</b>	544	451	246	56
	ruminating_standing	6	21	3	0	16	13	132	<b>5271</b>	65	9	15
	standing_resting	133	107	129	301	145	191	293	130	<b>16389</b>	166	309
	vigilance	38	137	115	79	203	93	305	199	557	<b>16809</b>	182
walking	77	50	242	1378	74	101	98	59	256	63	<b>19502</b>	

Columns represent the predicted behaviors; rows represent the actual observed behavior the validation data set.  
Bold values are the number of observations correctly predicted by the model.

TABLE 5 Confusion matrix for orientation dependent features with 20 seconds running mean including all behaviors below 0.1% proportionally of the data set.

		Predicted behaviors																			
		allogrooming	butting	calf_suckle	defecating	foraging_high	foraging_low	getting_up	laying_down	laying_resting	other	rub_scratch	ruminating_laying	ruminating_standing	self_grooming	shaking	standing_resting	throw_head	vigilance	walking	
Actual behaviors	allogrooming	3538	0	8	0	7	2	0	0	3	2	0	3	3	2	0	12	0	0	0	5
	butting	0	806	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	calf_suckle	0	0	4147	0	3	0	0	0	0	1	0	3	3	0	0	0	0	0	0	0
	defecating	0	0	0	262	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	foraging_high	6	3	5	0	7261	88	2	10	13	3	0	1	21	5	0	11	0	3	16	24
	foraging_low	370	288	179	29	3972	72446	119	129	149	231	136	204	351	209	58	962	12	24	569	2055
	getting_up	0	0	0	0	0	0	589	0	0	0	0	0	0	0	0	0	0	2	0	0
	laying_down	0	0	0	0	0	0	0	490	0	0	0	0	0	0	0	0	0	0	0	0
	laying_resting	57	11	48	0	61	40	38	59	19881	41	41	553	63	66	74	207	13	24	426	105
	other	0	0	0	0	0	0	0	0	0	1118	0	3	0	0	0	0	3	0	0	0
	rub_scratch	0	1	0	0	0	0	0	0	0	1	773	0	0	0	1	0	0	0	0	1
	ruminating_laying	469	73	176	5	159	22	113	7	773	99	129	52143	981	118	460	454	8	267	514	219
	ruminating_standing	4	0	12	2	5	0	1	4	0	1	0	12	5453	0	12	20	5	9	8	3
	self_grooming	0	0	0	0	0	0	0	0	0	0	1	0	0	1079	0	0	0	1	0	0
	shaking	0	0	0	0	0	0	0	0	0	0	0	0	1	0	592	0	0	0	0	0
	standing_resting	246	101	79	31	304	352	29	40	112	248	57	148	142	186	19	15540	41	29	196	393
	stretching	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	390	0	0
	throw_head	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	421	0	0
	vigilance	78	5	241	45	277	182	24	6	172	69	60	225	300	32	47	545	9	99	16106	195
	walking	105	69	40	65	733	1410	43	14	82	137	53	154	202	98	13	535	32	10	188	17917

The columns represent the predicted behavior; rows represent the actual observed behavior. Bold values are the number of observations correctly predicted by the model.

(Mansbridge et al., 2018; Chang et al., 2022). In our study we did not find such a decrease. An explanation might be that we excluded all behaviors shorter than 5 seconds, resulting in a large enough difference in mean and variance of the features for those behaviors for successful classification. Furthermore, the large number of observations in the minority classes (rarer behaviors) across individuals might have contributed positively during the training of the model, resulting in high model performance.

Finally, we predicted that adding more behaviors would affect model performance negatively and expected that the addition of behaviors would lead to loss of model performance (H2) as it has been shown in previous studies (Vázquez Diosdado et al., 2015; Lush et al., 2018). Contrary to our prediction, we found that models performed well with an increase of behaviors and could accurately predict less frequent behaviors such as head butting, throwing head and shaking. Less frequent behaviors were observed for fewer individuals than more common behaviors, which may lead to a stronger impact of individual-specific accelerometer signatures in the random forest models. We addressed this through class weighting, and individual-based cross validation. Even though there was variation in prediction success across individuals and behaviors, the overall model performed similarly well as with the 5-fold (i.e. with random 80/20 data split) cross-validation model.

This study's sample size of individuals is larger than most accelerometry classification studies of free-ranging cattle (Chapa et al., 2020; Kour et al., 2021). Riaboff et al. (2022) recommended using a minimum of 10 animals and emphasized more robust analysis with at least 25 animals and a variety of breeds and farms. While we exceeded this recommendation ( $n = 38$  individuals distributed on four breeds and four farms), we did not specifically account for breed, farm or individual characteristics such as body weight or age, as this would require an even larger sample.

Interestingly, we were able to differentiate between behaviors that we expected to have similar accelerometry signatures, such as laying ruminating and standing ruminating. When looking at posture, cattle laying causes the angle of the accelerometer to vary slightly compared to when they are standing, as the electronic housing often leans against the individual's chest. Similarly, we could identify vigilance behavior, which is likely due to our decision rule defining individuals as being vigilant only when no other behavior happened (Supplementary Figure 1).

Often, scientific studies develop models and tools that are appropriate for experimental settings, but too expensive or impractical to be used for commercial settings. Our results based on the accelerometers contained in the commercial Nofence collars open up for a range of end-user applications. For example, these could be Nofence tools for easy handling by the customers, such as a built-in algorithm in the collar converting accelerometer data directly to behavioral states or to time budget summaries, which could be continuously transmitted to the farmer. This could allow for an easy and fine-scale supervision and monitoring of free-ranging cattle in remote areas or dense habitats. Furthermore, the success in classification of ruminating, vigilance and social behaviors could contribute to the study of free-ranging cattle welfare, stress and productivity, through the quantification of precise nutrient intake and energy expenditure.

In conclusion, our study succeeded in categorizing high resolution accelerometer data into behaviors for free-ranging cattle in rugged terrain of the boreal forest. Not only were collar deployment errors confirmed to not significantly impact model performance, but our models also showed success in detecting more behaviors than previously published, including less frequent behaviors other than resting, grazing, ruminating and walking. Calibrating such data with an array of different behaviors makes a valuable contribution to livestock precision farming in extensive rangeland systems. It may allow farmers to monitor the welfare of their animals continuously and to detect non-normal behaviors caused by e.g. diseases or carnivore attacks.

## Data availability statement

The data and R scripts to replicate the models of this study are openly available in Dataverse NO at <https://doi.org/10.18710/ND4CLL>.

## Ethics statement

Ethical review and approval was not required for the animal study because this study used commercially available GPS/virtual fence collars in Norway and is approved by the Norwegian authorities for use on cattle. Written informed consent was obtained from the owners for the participation of their animals in this study.

## Author contributions

EV, LJN, MS, BZ, and ALE conceived the study. BZ and ALE secured the funding. LJN conducted the filming and video analysis. EV and MS conducted the accelerometry analysis, with additional support of OD. EV and LJN drafted the manuscript. MS, BZ, AH, MT, OD, ALE reviewed and commented on the initial drafts. All authors contributed to the ideas and edits to the manuscript and approved the submitted version.

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## Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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## Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fanim.2023.1083272/full#supplementary-material>

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