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Validation of inertial measurement units to detect and predict horse behaviour while stabled

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Abstract

Background: Musculoskeletal injuries are observed in Thoroughbred racehorses and may become catastrophic. Currently, there are limited methods for early detection of such injuries. Most injuries develop gradually due to accumulated damage, providing the opportunity for early detection. Horses experiencing pain or lameness may exhibit changes in behaviour so the development of an objective, real-time system monitoring horse behaviour may enable detection of bone injuries before catastrophic failure.

Objectives: To determine whether intensive observational methods of assessing horse behaviour can be replaced by use of inertial measurement units (IMUs).

Study design: Validation study assessing IMU use against video observation.

Methods: Six hospitalised Thoroughbreds (algorithm training data) and 19 Thoroughbred racehorses in-training (algorithm testing data) were equipped with an IMU placed on the lateral side of both forelimbs (left fore, LF; right fore, RF) and monitored in a stable for 4 h. An algorithm was developed to classify behaviour and then validated against video recordings.

Results: Standing was the most prevalent behaviour (LF 88.8%, 95% confidence interval [CI] 88.7–89.0; RF 88.5%, 95% CI 88.4–88.7). IMU classification of recumbent and standing activities showed excellent agreement (sensitivity) with video observation (>98%). This was followed by stepping (LF 89.4%, RF 85.5%) then weight-shifting (LF 54.3%, RF 61.5%). Predictions from the algorithm showed misclassification of 2.5% (LF 5500/225 352, RF 5218/210 170). Excluding standing, misclassification was 6.8% (1705/25 158) and 7.5% (1812/24 077) for the left and right forelimbs, respectively, with pawing and weight-shifting most frequently misclassified.

Main limitations: Increasing the number of horses and types of behaviours observed may improve predictions.

Conclusions: IMUs displayed a high sensitivity to movement on a small number of horses, and with further validation they have the potential to effectively monitor behaviour of racehorses in training. However, more sensitive methods may be needed to validate the classification of weight-shifting behaviour. Future studies should evaluate the association between each behaviour and musculoskeletal injury.

KEYWORDS
horse, IMU, orthopaedic pain, racehorse, Thoroughbred, video monitoring

1 | INTRODUCTION

Musculoskeletal injuries are the most common cause of lost training days and early retirement in racehorses, resulting in substantial economic impact to owners and trainers.[1,2] Most injuries in racehorses are due to tissue fatigue, developing gradually as bone or tendon integrity is overcome by repetitive load.[3] For bone, this is evidenced by post-mortem examinations revealing pre-existing pathology for fracture including periosteal callus formation, focal bone resorption and microdamage.[4–6] Because most injuries develop over time, there is an opportunity for early detection.[4,6] The use of diagnostic imaging techniques to detect early injury has been investigated, but low specificity, high cost and logistics limit their use for screening large numbers of horses.[7–10] Additionally, a trend towards increased racing stable size (number of horses per trainer) over the past decade makes close monitoring of horses more challenging.[11,12] Continuous observation is not feasible nor practical for most racing stables, and horses tend to hide their discomfort in the presence of observers.[13] Therefore, an automated, objective monitoring system to aid in the assessment of racehorse behaviour is needed.

Orthopaedic pain, commonly expressed as lameness in horses, is also associated with changes in behaviour including weight-shifting,[14] pawing[15] and restlessness.[16] The development of an objective, preferably real-time, system to monitor horse behaviour may enable the early detection of bone injuries before more overt clinical signs developing. Numerous measures to evaluate pain have been developed to score severity based on ordinal or simple descriptive scales, including composite multifactorial scales and facial expressions.[15-24] Horses in pain are shown to spend more time inactive and those with known orthopaedic pain have been observed unloading one limb, pawing and weight-shifting, although behaviours such as pawing are not specific to orthopaedic discomfort.[14-17] Further, rather than singular expressions of behaviour in horses, composite and facial expression-based pain scales show promise, at least for acute pain.[25] A combination of behaviours (posture, weight-bearing) and physiological signs (temperature, heart rate) were found to be associated with movement asymmetry from the Equine Pain Scale and Composite Pain Scale.[26] Subtle signs of orthopaedic pain have also been recognised in a first attempt using pose estimation of raw video data, trained on a data set of facial and upper body poses in horses with acute experimental pain.[27] However, current methods of intermittent monitoring may not accurately detect the frequency of pain-related behaviours.[17]

Wearable inertial measurement units (IMUs) use orientation and acceleration to interpret activity.[28–31] IMUs have been used to detect Parkinson's disease in humans,[32] and to study movement of marine, terrestrial and airborne animals.[33–36] Movement is recorded as acceleration signals and analysed by machine learning tools to identify patterns that can be used to discriminate behaviours. Algorithms have been developed and validated to classify dog behaviour with excellent agreement (>0.90),[37] detect lameness in sheep with an 82% accuracy,[38] monitor lying behaviour in cattle[39] and predict foaling in broodmares.[40] More recently, IMUs have been used to predict step count in horses under stall confinement with excellent agreement (>0.99),[41] and assess changes in postural sway for horses with induced lameness.[42]

Effective remote monitoring of horses could be used in racing stables to detect subtle changes in behaviour. The objective of this study was to determine whether IMUs are sensitive enough to detect horse behaviours when compared with intensive methods, such as constant observation, in what would be considered a healthy population, as orthopaedic pain can be sub-clinical. We aimed to develop an algorithm to classify horse behaviour and (1) determine the accuracy and precision of the behavioural events predicted by IMUs; and (2) validate their use to quantify posture and behaviour, specifically, in detecting static orientations of standing and recumbency as well as dynamic movements of stepping, pawing and weight-shifting.

2 | MATERIALS AND METHODS

2.1 | Study population and environment

Twenty-five Thoroughbred horses were recruited from the University of Melbourne Equine Centre (UVet) ($n = 6$) and 1 Victorian registered racehorse trainer ($n = 19$). Six horses recruited from UVet were utilised for algorithm development (mean age 3.7 years, standard deviation (sd) 2.2 years). We reasoned that this population would allow for observation of horses likely to be exhibiting signs of pain and/or discomfort in a closely controlled environment. For validation, the developed algorithm was then tested using video recordings of 19 horses in a typical racehorse training stable environment that met the inclusion criteria; (1) Thoroughbred racehorse; (2) ≥3 years and (3) deemed fit for race training. This test population consisted of $n = 3$ females, $n = 13$ geldings and $n = 3$ colts and stallions, with a mean age of 3.8 years (sd 1.07).

Horses were confined to individual $360 \times 370\ mm^2$ stables for the recording periods. Stables had visual access to neighbouring horses by means of open metal bars dividing the sides of stalls (above ~1.3 m of solid wall) and on the front wall inwards to a breezeway. Rear walls were solid with no visible distractors. Ad-lib hay and water were available and positioned either on the ground or at chest height.

Horses were provided with hard feed twice daily, morning and late afternoon.

2.2 | Sample size analysis

Estimation of sample size was based on a previously published validation of motion sensors in dairy cattle that identified lying, standing and moving (four calves in training data set; five calves in validation data set). As that study found that the motion sensor accurately measured high-prevalence behaviours, but less accurately measured low-prevalence behaviours, we increased the number of horses used (6 training; 19 validation) for this current study.[43]

2.3 | Accelerometer data

Horses were equipped with two 500 Hz nine axis IMUs (length: 40 mm; width: 28 mm; depth: 15 mm; mass: 12 g; accelerometer range: ±16 g; gyroscope range: ±2000 degree per second ($^{\circ}s^{-1}$); Vicon). Sensors were positioned on the lateral side of both metacarpi (left fore, LF; right fore, RF), secured in a horse boot with a purpose-built Velcro pouch (Figure 1).

The duration of data collection was limited to the battery life of the sensors (<5 h). Therefore, data were collected in varied 4 h time windows, ranging from start times of approximately 10:00–22:00, as dictated by stable activities and horse availability, avoiding active periods such as trackwork, with 8/19 horses being fed within the time window that they were monitored. A mobile application (IMeasureU, Vicon) was used to start and stop data capture.

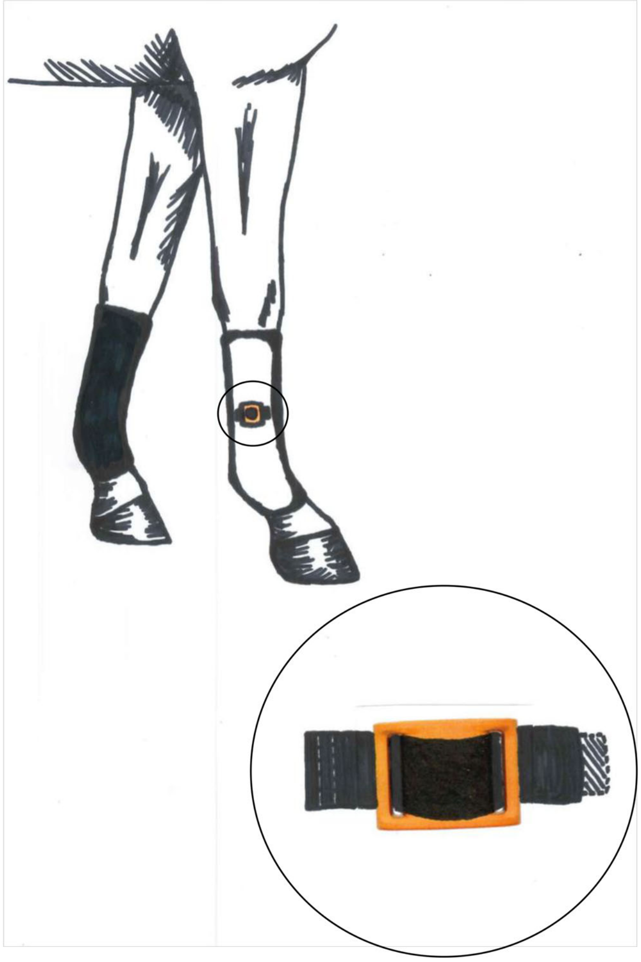

FIGURE 1 Depiction of boots with inertial measurement unit (IMU) placement. Sensors were positioned on the lateral side of both metacarpi (left and right fore), secured in a horse boot and stitched into a purpose-built Velcro pouch (inset).

2.4 | Video analysis

Video footage was recorded using a video camera (TECHview 1080p) mounted to a bracket that was securely fastened to the stable wall in one corner at a height of 2.4 m, which allowed for a view of the entire stable (101°). The mean footage for each horse was 224 min (sd 37.6). The sensors were tapped by hand multiple times in view of the camera to provide a time stamp that was used to synchronise the video footage with the IMU data.[30]

2.5 | Data processing and algorithm development

Data processing and algorithm development was conducted using MATLAB version R2018a (MathWorks). MathWorks, Natick, Massachusetts, United States.

Sensor data were extracted from the IMUs and imported into MATLAB. A custom-designed MATLAB script was used to process the data. The z- and x-axes from the sensor of the left forelimb were multiplied by -1 to convert data equivalent to that of the right forelimb.

Data were collected from hospital-admitted horses ($n = 6$) and used to train the algorithm (training data). The video recording was used to manually label time frames from sensor data to a behaviour class. The time stamp allowed one observer (KA), with experience working in Thoroughbred racing stables and as a post-graduate trained in equine behavioural annotation, to coordinate IMU time with video footage. For each movement on IMU, the start time was recorded and labelled according to the behaviour observed on video in 1-s intervals.[29] This time interval was chosen because it has previously been reported to be sensitive to detection of movement for most behaviour classes.[34]

We defined six basic behavioural classes. Each behaviour was encoded from 1 to 6: (1) left recumbency; (2) stepping; (3) pawing; (4) standing; (5) weight-shifting; and (6) right recumbency (Table 1). Behaviours were recorded based on the 1-s time-sampling interval. For recumbency, stepping, and standing they were based on previous studies comparing IMU recordings to video observations in cattle. Recumbency was defined as the animal either in lateral or sternal recumbency for the entire 1 s; and stepping as a minimum of one complete forward or backward progressive step.[44,45] Pawing was defined as pawing the ground or air or pointing or hanging the limb, and weight-shifting as changes in weight distribution or shifts, muscle tremors or non-weight bearing of either limb per Bussières et al.[15]

Each classified behavioural observation was allocated to a row number which was found by multiplying the time in seconds by 500 (because the data was recorded at 500 Hz; each second contained 500 points). Five features were calculated using a moving window calculation for the time interval across the entire array; including mean, median, minimum, maximum and sd. The five features were calculated for each of the eight columns, consisting of six acceleration signals (acceleration *x*, *y*, *z*; gyroscope *x*, *y*, *z*) and an additional two resultant vectors calculated using the Pythagorean method. These calculations were allocated to a behaviour and used to train machine learning classifiers. Each classifier was evaluated using 10-fold cross-validation and the accuracy of each was determined.[46]

TABLE 1 Description of broadly classified behaviours observed on video recordings in $n = 25$ Thoroughbred racehorses stabled at rest

Behaviour	Description
Left recumbency	The horse is in sternal or lateral recumbency with its left side down for >3 s, including behaviour such as rolling.
Stepping	Progressive movement of hoof from one location to another one.
Pawing	Non progressive movement. Continuous action of digging with one limb with the horse otherwise stationary.
Standing	Standing on both forelimbs without unloading or moving (≥1 s)
Weight-shifting	Non progressive movement. Action of unloading weight from one limb to another (not necessarily taking a limb off the ground), often continuous between left forelimb and right forelimb.
Right recumbency	The horse is in sternal or lateral recumbency with its right side down for >3 s, including behaviour such as rolling.

2.6 | Validation

The developed algorithm was used to predict behaviour in $n = 19$ horses in race training (unlabelled test data set) using patterns recognised from the previously labelled training data set.[36,46] The predicted behaviours from the algorithm were blinded to the observer (KA), who manually classified behaviour per second from the video to one of the six defined behaviours. If behaviour could not be recorded because the limb of interest was obscured, the data was recorded as missing. Abnormal behaviour, that is, if activity could not be classified (e.g., sudden movement to the right), was recorded and excluded from analysis. Observations where the sensor slipped, malfunctioned, or did not record data (all observations for the right forelimb of one horse [HorseID 18] and $n = 313$ observations across various horses) were also excluded from analysis.

An internal-clock drift in the IMU was corrected using a time stamp to detect the difference between true and IMU time. Each sensor was manually calibrated at consistent intervals based on the correction factor determined. Since the time resolution of the device was 1-s, the correction was implemented in the data as

TABLE 2 Summary information about the observed behaviour sequences of both left and right forelimb of $n = 19$ individual Thoroughbred horses in race training monitored in a stable

	Left limb observed		Right limb observed	
	Mean (sd)	Min, max	Mean (sd)	Min, max
Total length of observation (s)	12 093 (2149)	8512, 16 214	11 886 (2095)	8415, 14 763
No. of transitions	448 (165)	231, 982	431 (140)	230, 725
States observed (max = 6)	4 (1)	3, 6	4 (1)	3,6
Duration of each behaviour (%)[a]				
Left recumbency (8/19)	4.4 (8.2)	0, 29.8	4.7 (8.5)	0, 29.9
Stepping	3.5 (2.0)	1.5, 9.8	3.5 (2.0)	1.8, 9.4
Pawing	0.1 (0.1)	0, 0.2	0.2 (0.2)	0, 0.7
Standing	89.0 (7.7)	66.6, 97.9	88.7 (7.6)	66.7, 97.3
Weight-shifting	1.2 (0.7)	0.1, 2.6	1.3 (0.8)	0.1, 3.5
Right recumbency (4/19)	1.9 (3.9)	0, 11.2	1.8 (4.0)	0, 12.4
Entropy[b]	0.22 (0.1)	0.06, 0.42	0.23 (0.1)	0.08, 0.42
Complexity[c]	0.09 (0.1)	0.04, 0.16	0.009 (0.02)	0.05, 0.13

[a]The percentage of time spent in each state of behaviour during the observational hours, which include weight shifts before and after stepping which were excluded from analysis.
[b]A measure of diversity of states that compose the sequence, based on time spent at different states (where 0 = one behaviour observed and 1 = equal time spent at each state).
[c]Combines entropy and number of transitions.

occasional repeats of the same time, or occasional 1-s skips, as previously reported.[47]

The transitional period between standing and stepping was frequently classified as weight shifts (LF 55.8%, 4087/7316; RF 50.7%, 3623/7143 of total weight shifts). To account for this misclassification, a variable to exclude weight shift movements predicted before and after stepping behaviour was generated. A period of 5 s following the transition of recumbent to standing was not used in validation analysis because behaviour displayed could not be defined.

2.7 | Data analysis

Statistical analyses were conducted in Stata/IC version 15.0 (StataCorp).[48] The unbalanced ratio of behaviours meant the accuracy for all classifications was excellent and not informative to the overall performance of the algorithm. Therefore, we evaluated the performance of the algorithm based on its ability to correctly predict individual behaviours, including sensitivity and precision, as previously done by Martiskainen et al.[49] A confusion matrix describing the performance of the algorithm at classifying behaviours was generated.[46]

Sensitivity (true positive/[true positive + false negative]), and precision (true positive/[true positive + false positive]) were determined to assess the accuracy of the algorithm to predict horse behaviour in the test data ($n = 19$), by comparing the video observation to the behaviour predicted. Continuous data were assessed using the Shapiro–Wilk test, and as the majority were normally distributed, all data were reported as mean and standard deviation. Sequence index plots were generated in Stata (StataCorp). Sequence analysis was conducted in R using the package TraMineR (R Foundation for Statistical Computing).[50,51] The duration of each behaviour was calculated as a mean of observed behaviour for each behaviour. For recumbency behaviour, the duration percentage was a mean calculated from only those horses that were recumbent at least once.

3 | RESULTS

3.1 | Training data

The performance of the behaviour classifier algorithm on the training data is presented as a confusion matrix in Table S1, with sensitivity ranging from 80.3% to 96.7% and precision from 85.9% to 100% for each behaviour. Left recumbency had the highest precision, followed by standing, pawing, weight-shifting, stepping and right recumbency. Stepping and pawing had the lowest sensitivity.

3.2 | Test data

Tables 2 and S2 describe the summary data recorded from 19 individual horses for observations, transitions and duration of behaviours.

TABLE 3 Total agreement between predicted and observed behaviour $n = 19$ Thoroughbred stabled horses over a 4-h monitoring session per second. Predicted behaviours were classified using inertial measurement units placed on the left fore (LF) and right fore (RF) metacarpi of each horse. Observed behaviours were classified using video recordings.

	Observed													
	Left recumbency		Stepping		Pawing		Standing		Weight-shifting		Right recumbency		Total	
	LF	RF	LF	RF	LF	RF	LF	RF	LF	RF	LF	RF	LF	RF
Predicted														
Left recumbency	**11 477**	**11 466**	1	0	0	0	0	0	2	3	1	3	11 481	11 472
Stepping	13	13	**5805**	**5075**	31	56	1113	895	477	377	1	0	7440	6416
Pawing	2	1	29	9	**79**	**56**	13	3	4	6	1	0	128	75
Standing	2	1	441	528	3	0	**196 399**	**182 687**	479	483	0	0	197 324	183 699
Weight-shifting	0	8	216	323	1	1	2669	2508	**1143**	**1391**	1	0	4030	4231
Right recumbency	0	0	0	0	0	0	0	0	0	0	**4949**	**4277**	4949	4277
Total	11 494	11 489	6492	5935	114	113	200 194	186 093	2105	2260	4953	4280	**225 352**	**210 170**

Behaviours not classified within the six classes, behaviour not observed, and behaviour detected in the second before and second after 'stepping', were excluded from calculations of agreement. Other behaviours not analysed included: shake, roll, kick, lift leg and scratch leg ($n = 935$ s).

Video observation detected standing as the most dominant behaviour pattern in the test data set, with prevalence of 88.8% and 88.5% for the left fore and right fore, respectively (Tables 3 and 4), followed by recumbency (left-sided recumbency prevalence of 5.1% and 5.5% and right-sided 2.2% and 2.0%) and stepping (2.9% and 2.8%, respectively) (Table 4). Over the complete observation period, 57.9% of horses (11/19) were recumbent for a period of more than 3 s, most of which occurred during the afternoon (between 3.00 PM and 5.00 PM) or evening (after 8.00 PM) (Figure 2). The mean total recumbent time for all horses was 14.5 min (sd 19.4; range 0–70.9). One horse was recumbent for 27.5% of the observational period (70.9/257.6 min).

Greater than 60% of behaviour states observed were followed by the same behaviour state in the next recorded second, with the exception of weight-shifting (Table S3). Weight-shifting was most often followed by standing (47%) or more weight-shifting (42%). Calculations of transition rates when repeated events in sequence were ignored showed a high probability that stepping (90%) and weight shifts (81%) were followed by standing. The longitudinal characteristics of sequences between horses are illustrated (Figure 2), which can be used to interpret how individual horses change behaviour state over time.

The total agreement between predicted and observed behaviours (Table 3) was used to calculate precision (proportion of positive predictions that were correct) and sensitivity (proportion of the positive cases that were predicted positive) of the algorithm to predict each behaviour classification, stratified by limb (Table 4). Overall, precision varied from 28.4% (weight-shifting) to >99.9% (recumbency), and sensitivity varied from 49.6% (pawing) to 99.9% (recumbency). Standing and recumbency were predicted with a precision and sensitivity of >98% in both left and right limbs. Stepping behaviours were predicted with 78.0% and 79.1% precision and 89.4% and 85.5% sensitivity for the left and right forelimb, respectively. Compared with video observations, after exclusion of 1 s before and after stepping and abnormal observations, the predictions from the algorithm showed mean misclassification by horse of 2.6% for the left and right forelimb (LF sd. 1.6%, range 1.0, 7.8%; RF sd. 1.4%, range 1.2, 6.7%). Overall misclassification was 2.4% (5500/225 352) and 2.5% (5218/210 170) for the left and right forelimbs, respectively (total 2.5%). However, excluding standing (the most prevalent behaviour), overall misclassification was 6.8% (1705/25 158) and 7.5% (1812/24 077), respectively. Pawing

TABLE 4 Sensitivity, precision and prevalence as percentages and their respective 95% confidence intervals (95% CIs) of behaviours between video observation and algorithm prediction of behaviour in $n = 19$ stabled Thoroughbreds, stratified by limb

	Sensitivity (95% CI)			
Behaviour	**Left forelimb**	**95% CI**	**Right forelimb**	**95% CI**
Left recumbency	99.9	99.8–99.9	99.8	99.7–99.9
Stepping	89.4	88.6–90.2	85.5	84.6–86.4
Pawing	69.3	60.0–77.6	49.6	40.0–59.1
Standing	98.1	98.0–98.2	98.2	98.1–98.2
Weight-shifting	54.3	52.1–56.4	61.5	59.5–63.6
Right recumbency	99.9	99.8–100.0	99.9	99.8–100.0
	Precision (95% CI)			
Behaviour	**Left forelimb**	**95% CI**	**Right forelimb**	**95% CI**
Left recumbency	>99.9	99.9–100.0	99.9	99.9–100.0
Stepping	78.0	77.1–79.0	79.1	78.1–80.1
Pawing	61.7	52.7–70.2	74.7	63.3–84.0
Standing	99.5	99.5–99.6	99.4	99.4–99.5
Weight-shifting	28.4	27.0–29.8	32.9	31.5–34.3
Right recumbency	>99.9	99.9–100.0	>99.9	99.9–100.0
	Prevalence (95% CI)			
Behaviour	**Left forelimb**	**95% CI**	**Right forelimb**	**95% CI**
Left recumbency	5.1	5.0–5.2	5.5	5.4–5.6
Stepping	2.9	2.8–3.0	2.8	2.8–2.9
Pawing	0.1	0.0–0.1	0.1	0.0–0.1
Standing	88.8	88.7–89.0	88.5	88.4–88.7
Weight-shifting	0.9	0.9–1.0	1.1	1.0–1.1
Right recumbency	2.2	2.1–2.3	2.0	2.0–2.1

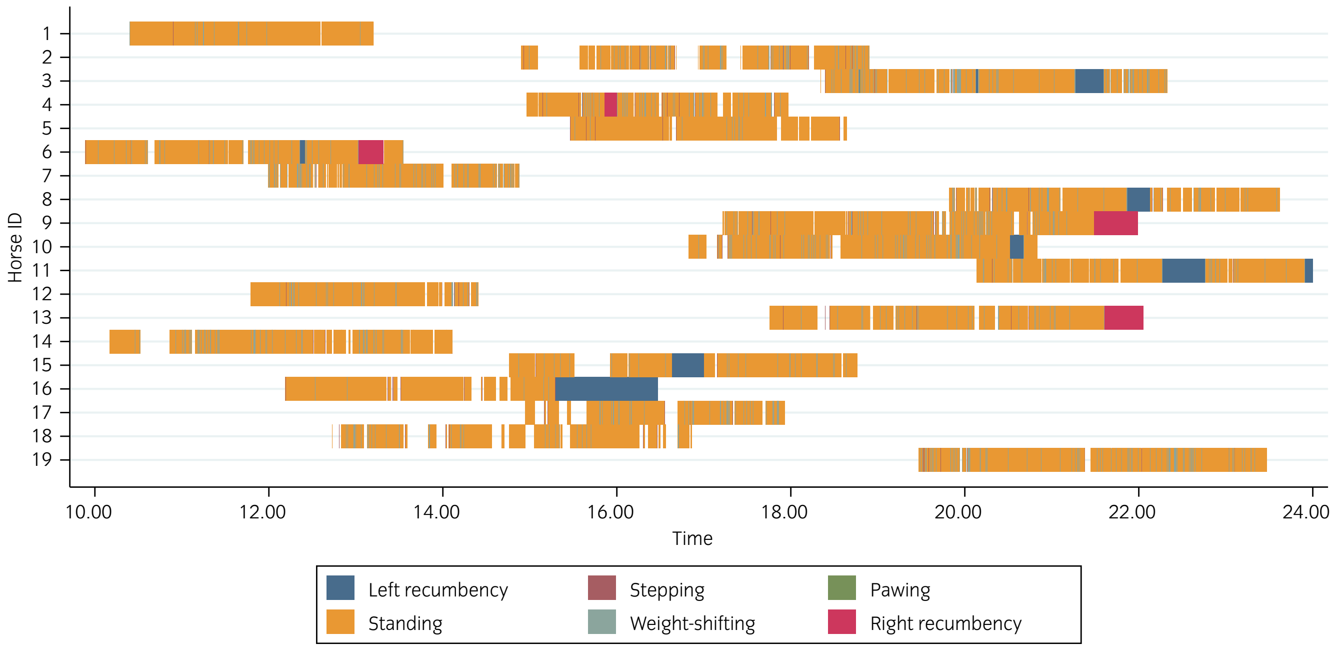

FIGURE 2 Sequence index plot demonstrating changes in behaviour states over time of Thoroughbred racehorses in training ($n = 19$). Changes in behaviour state are shown by changes in colour.

was most often misclassified as stepping (LF 27.2% and RF 49.6% of true positives). Weight-shifting was most often misclassified as either standing or stepping (LF 45.4%; RF 38.1% of true positives).

4 | DISCUSSION

Using IMUs, an algorithm was developed and validated to accurately identify horse behaviour, and therefore has the potential to replace current methods of observation and enable continuous monitoring. Using a supervised learning algorithm, we achieved >85% sensitivity for four behaviours: left recumbency, right recumbency, stepping and standing; and 50% to 69% sensitivity for pawing and weight-shifting. The overall performance of the device suggests it could be developed into a system able to monitor Thoroughbred racehorses in their stables, and over time may allow detection of subtle changes in behaviour patterns.

The horses in our study spent the greatest time standing (89%) and the least time pawing (<1%). A previous study observing stabled horses for 72 h (divided into 12-h segments over 6 days, with up to 4 h paddock time per day) found the majority of time was spent standing (55%) and grazing (24%). Assuming horses were standing while grazing, this totals 79%.[52] Our findings may be similar, though we did not independently categorise eating behaviours. Horses have been observed to spend most of their recumbent time in sternal recumbency rather than on their side.[52] We were able to differentiate between left and right lateral recumbency but we did not classify sternal recumbency separately.

The sensitivity for detecting recumbent and standing in this study was excellent (>98%), comparable to previous validation studies in cattle and horses (≥98%).[44,53,54] However, sensitivity for predicting pawing was much lower, with the right forelimb sensor correctly predicting only half of observed pawing episodes. Pawing movements can be brief, so mismatches between the sensor and human observation time recordings are more likely than for behaviours of a longer duration. Similar validation studies found that after slowing the recordings down to review disagreements, the device predicted correctly, and the observer was incorrect.[37] In our study, the video footage regularly replayed at 50% of real time, along with the recording of behaviour every second, was intended to help identify these rapid movements. Recently, a small study using observation and convolutional neural networks, found the largest contributors to a lower accuracy were the misclassifications of pawing, rolling and flank watching.[55] These behaviours were only performed by one horse during the collection of training data and therefore made up only 2.4% of the data set. The infrequent display of pawing limits training opportunities for classifiers. Additionally, individual pawing patterns were diverse, producing distinctive acceleration patterns for each horse, unlike the repetitive movement pattern observed during walking or recumbency. Therefore, larger input data sets are required for training algorithms to recognise pawing behaviour.

We placed the motion sensors on the forelimbs. This position was previously shown to achieve the highest accuracy for discriminating between equine gaits, including walk, trot and canter.[56] Placement on the right forelimb vertical axis has been demonstrated to have excellent agreement (ICC 1.0) between sensor-based step count and video-based step count for horses confined to stalls.[41] Placement of a motion sensor around a cow's neck has been successful for recognising rumination and eating behaviours,[49,57–59] but sudden head movements can disrupt recognition of other behaviour patterns and collars may move freely, independent of animal movement.[58] Additionally, sensors placed on the neck have difficulty differentiating standing and sternal recumbency because the orientation of the axis does not change.[49] Forelimb placement, as in the present study, can differentiate these postures using the perpendicular difference between x- and y-axes.[45] Robert et al. placed the motion sensor on the hindlimb of cattle and reported excellent agreement with video for lying and standing (99.2% and 98%, respectively).[44] However, walking classification accuracy was significantly lower (67.8%). Sensors placed on the ear, collar and leg yielded different prediction accuracy for lameness in sheep. Leg-mounted sensors cannot differentiate standing from grazing, unlike ear-mounted sensors which can distinguish non-grazing standing with a 96% prediction accuracy.[38] As eating and drinking were not classified in this current study, concurrent behaviours, particularly those like eating hay could confound the detection of weight-shifting. Additional sensors strategically placed could be utilised to detect a movement pattern unique to one behaviour that discriminates it from others. Although multiple sensors would not be practical in a racing stable, further investigations would be required to determine if different sensor placement could improve prediction accuracy. Future work could include classifying more behaviours that are performed by horses and associated with stress or discomfort such as eating behaviour or time spent in sternal or lateral recumbency, physiological signs, additional placement of IMUs on hindlimbs to potentially improve detection of weight-shifting behaviour, body behaviours (including posture, head position, location in the stable, focus, and interactive behaviour), or integration of other algorithm-based pain assessment scales such as those used for facial assessment of pain.

The algorithm showed 54% and 62% sensitivity for left and right forelimbs, respectively, in correctly predicting observed weight shifts, however, precision was only 28 and 33%, respectively. Misclassified weight shifts predicted by the algorithm were most commonly recorded by the observer as standing. This may be due to the high sensitivity of the IMU system to detect small accelerations (sampling rate: 500 Hz) compared with the temporal resolution of the human eye (15–20 Hz).[60] It is difficult to determine true sensitivity when the gold standard is subjective and objective tools have shown higher sensitivity to detect clinical signs before human diagnosis.[61,62]

Weight-shifting was also more difficult to classify when compared with behaviours that occurred over longer periods of time without change. The high probability of a transition between stepping, standing and weight-shifting (Table S3) may account for the difficulty in differentiating between individual weight shifts as an independent (primary) movement or as a transitional (secondary) behaviour. These three behaviours in particular can be both a primary behaviour or secondary element of another behaviour, and thus in future studies it is important to distinguish between progressive stepping such as walking from one locale to another or nonprogressive stepping that is associated with, for example, weight-shifting or pawing; or pawing prior to rolling or recumbency. In an attempt to label weight-shifting where it was deemed a primary behaviour, we excluded weight shifts 1 s before and 1 s after stepping behaviour, although this time period may not effectively account for all transient detections of weight shifts (such as before and after pawing). Therefore, it may be necessary to make improvements to the algorithm to increase sensitivity for weight-shifting as a primary movement, or to label these behaviours separately in the context of being primary or secondary. Further, behaviours occurring concurrently to those recorded by the IMU, but that were not accounted for in this study (e.g., eating while standing or weight-shifting), may also require separate labelling. Other solutions may include employing more sensitive means of validating weight shifts that do not rely on visual classification (e.g., force plates),[63] accounting for the behavioural states over a longer time period preceding and following standing, or investigating alternatives such as using a single wither sensor to detect mediolateral postural sway as an indicator of subtle weight shifts in limb pairs as has been used to identify horses with constrained postural control.[42] As well as investigating associations between occurrence of specific behaviours with orthopaedic pain in future studies, transition and variability of behaviour may also be important predictors of pain, warranting further investigation.

Our study showed higher sensitivity and precision than studies using 10-s intervals, except for walking which was comparable, most likely because walking can be a continuous behaviour and easily averaged over 10 s. We chose to classify behaviour at a time-sampling interval of 1 s attempting to obtain the highest sensitivity for subtle movements. Intervals of 1 s were used in dogs to achieve >95% accuracy for six of eight behaviours.[37] The combination of sampling rate and time interval used can influence the accuracy of detecting horse behaviour.[55] Eerdekens et al. showed an increase of time interval from 0.6 to 1.2 s resulted in significant improvements to predictive performance.[55] Robert et al. compared the accuracy of 3-, 5- and 10-s intervals to determine behaviour in cattle and found agreement between sensor and observation was higher in 3- (98.1%) and 5-s intervals (97.7%) compared with the use of a 10-s interval (85.4%).[44] High variations in readings recorded over 10-s intervals were thought to reduce accuracy.

This study had some limitations. Only one observer manually labelled the defined behaviours from video observation. Future studies should consider additional observers when labelling data to reduce errors associated with subjectivity and human perception. However, previous observational studies have assessed both intra- and inter-observer reliability with positive results; 97.4% intra-observer reliability (agreement) for one observer recording recumbency behaviours in cattle,[53] and no significant difference was found between observations of horses recumbency recorded by two observers.[54] Second, the accelerometer and gyroscope used in this study had a battery life of less than 5 h. Although adequate for validation purposes, this would be a limiting factor for the clinical applicability of its purpose as a 24-h monitoring system. Further, data were not collected from ~02:00 to 10:00, and avoided during active periods in the yard, thus different patterns of behaviours may be observed during these times. The algorithm was not sensitive enough to accurately identify stepping, and weight-shifting and pawing, as separate progressive and nonprogressive movements, respectively. Previous studies showed accuracy was only reduced by 5% when sampling rate was reduced from 200 to 25 Hz.[55] A reduced sampling rate would improve battery performance, but this would require further algorithm development. Investigation of the long-term use of IMU boots may require assessment for practical use. Finally, we used six horses in the development of the algorithm, and thus increasing the number of horses and types of behaviours, particularly those behaviours that are more varied and less prevalent, may improve predictions.

IMUs have the potential to objectively quantify behaviour of stabled racehorses, and with further validation, may be generalisable to the wider equestrian industry. Although the association between each behaviour and musculoskeletal injury is still unknown, the ability to document behaviour over time may allow the identification of patterns indicative of pathology. The overall performance of the algorithm we developed to determine horse activity was reasonable, but only for prevalent behaviour. Further algorithm development is required for infrequent behaviours such as pawing, and distinguishing distinct bouts of weight-shifting from those that are due to a transition to another behaviour.

AUTHOR CONTRIBUTIONS

Katrina Anderson conducted data collection and collation. Katrina Anderson, Ashleigh V. Morrice-West and Peta L. Hitchens contributed to the data analysis. All authors contributed to the study design, interpretation of results, preparation of the manuscript and gave final approval.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study, excluding video recordings that are identifiable, are available from the corresponding author upon reasonable request.

ETHICS STATEMENT

The study was approved by the University of Melbourne Animal Ethics Committee (Reference number 1814523). Written consent for this study was obtained from the horse owner or duly authorised agent for the owner.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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