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## Review Article

## Impact of the technology to monitor horse behaviour and health: a scoping review

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## ABSTRACT

Technology for monitoring behaviour and health of horses has evolved significantly, presenting new opportunities and challenges in equine management and healthcare. This scoping review consolidates recent findings on wearable sensors and non-contact technologies, discussing their benefits and limitations. Among these advancements, heart rate monitors stand out as a key point in equine monitoring. By tracking heart rate variability, devices help monitor cardiac autonomic regulation, optimise training regimens and allow early detection of cardiac issues, although accuracy can be compromised by inadequate placement or signal interference. Beyond heart rate monitors, wearable biometric sensors and smart stable systems are revolutionising equine care. Biometric sensors track vital signs, temperature, and activity levels, offering continuous monitoring of health data. However, challenges remain regarding data accuracy, device durability, and integration with existing systems. Non-contact technology like computer vision provides a non-invasive method of analysing images and videos to detect horses, recognise specific features and track movement over time. This technology helps monitor behavioural patterns, social interactions, and overall activity. In conclusion, the application of wearable and remote monitoring technologies has shown specific benefits in supporting equine welfare. This review presents an overview of current sensors that support daily horse management and promote animal health through the detection of behavioural changes. These metrics could prevent the development of more serious issues. However, addressing limitations such as accuracy, reliability, and privacy concerns is essential. Scientific validation is necessary for guaranteeing the effectiveness of these systems and to maximise their potential to improve equine health and performance.

## 1. Introduction

In recent years, animal welfare has become a topic of increasing interest, evolving into an issue of scientific, regulatory and ethical significance. This has stimulated intense research and development in a variety of areas, including laboratories, farms, zoos, companion animals and working animals. The increased attention reflects a growing awareness of the need to improve the living conditions of animals while promoting environmental sustainability [1–4]. Animal welfare is defined as a multidimensional concept that includes the physical and mental state of animals, reflected in their ability to adapt to environmental conditions and meet their natural needs, as determined by their genetic and behavioural traits [5–7]. This broad concept includes both

negative aspects, such as fear and stress, and positive aspects, such as comfort and satisfaction [6,7]. In equines, welfare assessment is still a challenge, given the complexity of integrating multiple indicators into a representative framework [5,7,8].

Traditionally, equine welfare has been assessed through direct observations and physical indicators such as body condition or the presence of injuries and physiological indicators such as blood concentrations of cortisol. Although useful, these approaches have significant limitations, including time needed for the assessment, necessity of training new assessors for ensuring reliable evaluation and inability to ensure continuous monitoring [9,10]. These limitations have led to an increasing exploration of innovative technologies for monitoring equine welfare. Over the past 15 years, the introduction of advanced

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technologies, such as wearable sensors and non-contact systems, has partially filled gaps in clinical practice. These tools, through continuous and non-invasive monitoring, allow for the collection of physiological and behavioural data, which can support detection of clinical issues [11]. However, despite significant advantages over traditional methods, even these technologies are not without limitations [3,9,12]. These technologies still face limitations in terms of measurement accuracy and the restricted range of variables that can be monitored in both an animal and user-friendly manner. Moreover, these issues include battery life, often prohibitive costs, and the need for significant storage space for collected data. In addition, issues related to animal comfort and susceptibility to environmental factors (e.g., physical obstacles, temperature, and humidity) pose additional challenges to their in-field application [13,14]. This scoping review, conducted according to the PRISMA Extension for Scoping Reviews (PRISMA-ScR) guidelines, aims to map and summarise currently available technologies for monitoring equine behaviour and welfare. We describe their operational characteristics, applications, accuracy, and limitations of these technologies, with a specific focus on two key aspects: validity and applicability.

## 2. Scoping review methodology

### 2.1. Search strategy, inclusion and exclusion criteria

The investigation approach for this literature review was based on the PRISMA Extension for Scoping Reviews (PRISMA-ScR) standards [15]. Using Web of Science, ScienceDirect, and Scopus databases, we carried out an extensive bibliographic search with a specific focus on the areas “Article title”, “Abstract”, and “Keywords” search fields. No geographic or temporal restrictions were applied during the searches.

The search criteria for the title, abstract, and keywords were as follows: (“equine” OR “horse” OR “horses”) AND (“monitoring” OR “tracking” OR “sensor” OR “wearable” OR “technology” OR “smart device” OR “health monitoring” OR “physiological monitoring”) AND (one of the search combinations listed below):

1. (“heart rate” OR “cardiac activity” OR “pulse”)
2. (“respiratory rate” OR “breathing rate” OR “respiration”)
3. (“temperature sensors” OR “infrared” OR “body temperature” OR “core temperature”)
4. (“accelerometer” OR “activity sensor” OR “motion sensor” OR locomotion sensor”)
5. (“GPS” OR “tracking system”)

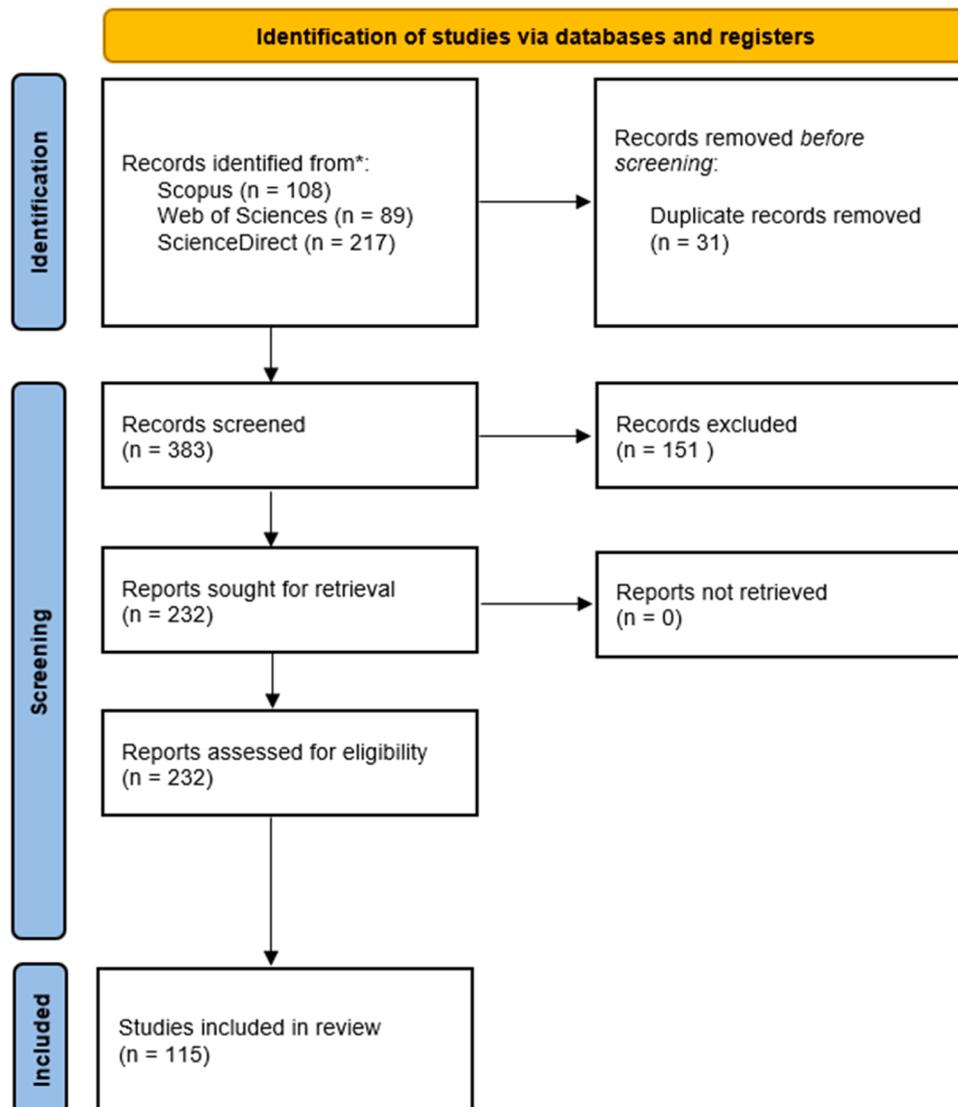


Fig. 1. Evidence selection flow diagram of database search, screening and inclusion (adapted from PRISMA-ScR [15]).

6. ("sound" AND "sensor")
7. ("vision" AND "camera") OR ("computer vision" OR "image analysis" OR "machine vision" OR "pattern recognition").

This first search led to the identification of 414 studies covering the period from 1995 to 2024. After removing duplicate entries, the total was reduced to 383. A Python script was used to process the data, remove duplicates, and save the final file in .csv format. Once the search in the database was completed, only peer-reviewed articles published in UK or US English, conference abstracts, and book chapters that described, evaluated, or applied technologies for equine monitoring were included. In line with scoping review methodology, no restrictions were applied by study design. Exclusion criteria also applied to research not addressing technology development or validation. The literature considered in this study was published up until 2024, which marks the conclusion of the search process. The full texts of the selected papers were then examined to confirm that they corresponded to our inclusion criteria, resulting in 115 publications determined to be pertinent for this evaluation. The selection procedure is presented in Fig. 1. using PRISMA-ScR principles.

## 2.2. Technologies identified and monitored parameters

Several devices used for the physiological and behavioural monitoring of horses were identified and analysed, categorised based on technology and type of application. These technologies were divided into two main categories: wearable and non-wearable. Wearable devices include technology for measuring heart rate, heart rate variability, respiratory rate, accelerometers and GPS devices. Non-wearable devices involve technologies such as microphones and computer vision algorithms.

## 3. Results and discussion

Following this selection process, a total of 115 documents were selected for in-depth analysis and their findings are incorporated into the later sections of the present review. This timeline reveals a rising trend in the number of publications over the years, reaching its peak in the years from 2021 to 2023, and still increasing, although the number of references for 2024 may be incomplete. The rise in publications from 2020 appears to be associated with the increasing scientific interest in machine learning, computer vision and deep learning. Reflecting this trend, the present review includes around 20 articles published since 2020 focusing on these technologies.

Fig. 2 illustrates a detailed visualization of the temporal distribution of these studies, starting from 1995.

Additionally, Fig. 3 shows the temporal network map of the most

frequently used keywords in studies focusing on the application, development and evaluation of technologies in the field of equine science over the last 10 years. The size of the nodes corresponds to the frequency of occurrences, while different colours indicate the years in which these keywords were most cited. As can be seen from the figure, recent trends appear to indicate a growing interest in research exploring machine learning, computer vision and Precision Livestock Farming (PLF) systems.

Geographically, the sensors reviewed were developed mostly in the United States and Europe. Overall, 42 different technologies were identified through the literature search. In detail, among the wearable devices, 7 were designed for measuring heart rate, 6 for estimating heart rate variability, calculated from heart rate (HR) or BP data, with some devices using electrocardiography (ECG) recordings and others using optical or other sensors, 18 for measuring body temperature, 11 for accelerometers and 4 for GPS devices. On the other hand, non-wearable devices include 3 microphones and 15 convolutional neural network (CNNs) or related datasets, most of which rely on camera or other vision-based acquisition systems for image or video analysis.

This classification introduces the next sections of the review, where wearable and non-wearable technologies were discussed. Fig. 4 illustrates the countries of origin of the majority of the sensors listed in the review. Most providers are based in the United States ( $n = 18$ ) and United Kingdom ( $n = 5$ ), followed by Finland ( $n = 2$ ), France ( $n = 2$ ) and Japan ( $n = 2$ ). Other providers from other countries, such as Ireland, Canada, Taiwan, Netherlands, Sweden and Switzerland have only one technology recognised.

### 3.1. Wearable devices

#### 3.1.1. Heart rate and respiratory rate sensors

A total of 19 articles were analysed in this section, from which we reported 12 devices relevant to this specific area of application.

Heart rate sensors are essential tools for monitoring the cardiac autonomic regulation and identifying changes in the physiological stress response in horses over time. They allow the capture of dynamic fluctuations influenced by environmental and individual factors [16,17]. However, collecting accurate HR data requires careful sensor placement and continuous quality control. These sensors have demonstrated significant potential in improving veterinary monitoring practices, as they can provide valuable insights into the horses' overall health in response to various stimuli [18,19]. In equine applications, there are different heart rate sensors including ECG sensors, photoplethysmography (PPG) sensors, and accelerometer-based sensors [18]. ECG sensors detect the electrical activity of the heart using electrodes placed on the horse's body, providing comprehensive ECG waveforms, HR, and heart rate variability (HRV) [20]. These tools are primarily used for diagnosing

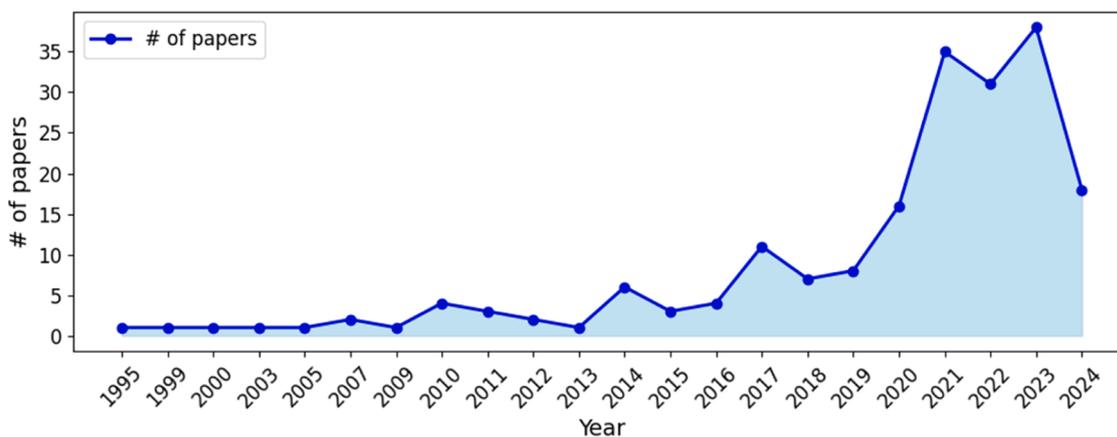


Fig. 2. Temporal trend of the papers included in the review.

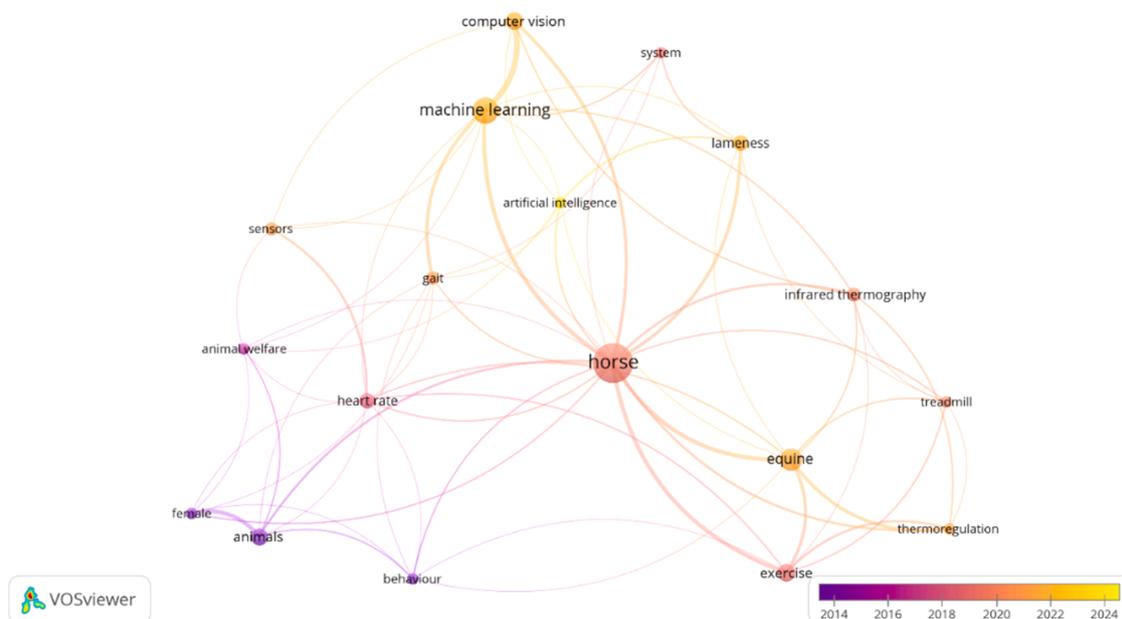


Fig. 3. Temporal network map of the most used keywords as extracted by the papers included in the review. The size of each node increases based on frequency of appearances while the different colours represent the years with the highest occurrences.

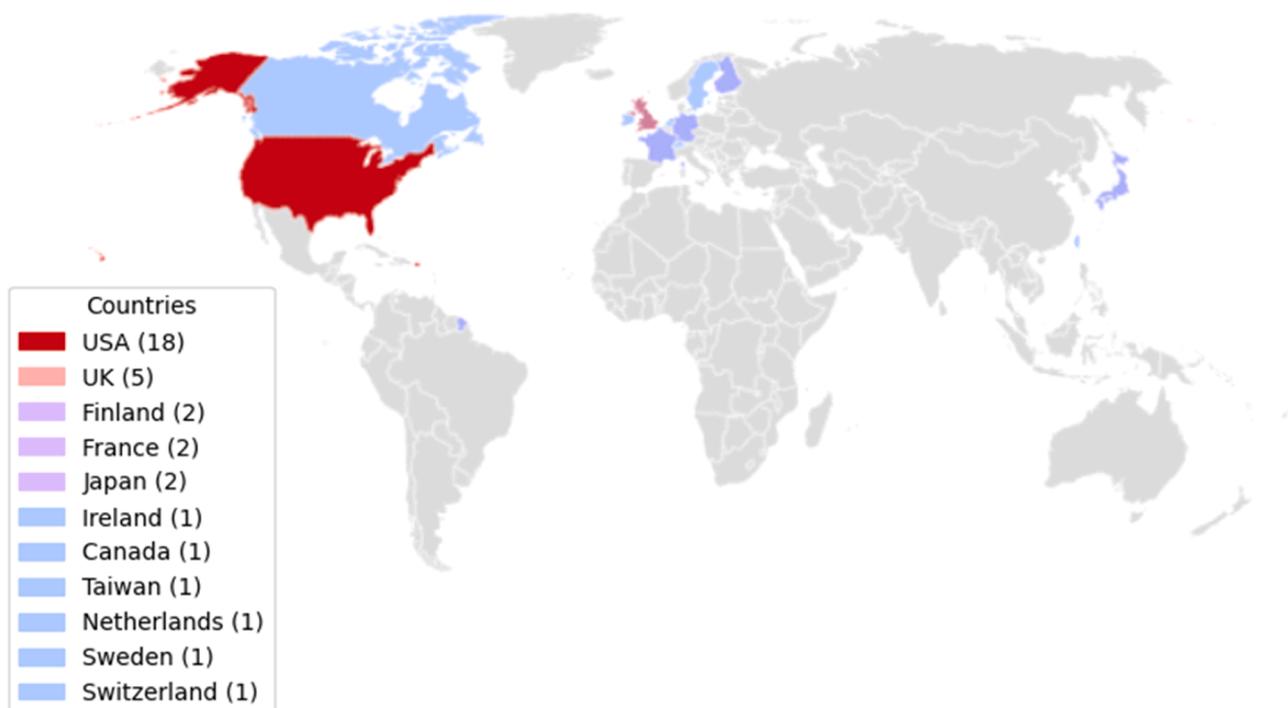


Fig. 4. Geographical origins of the PLF technologies included in the paper.

arrhythmias and other cardiac conditions. They also play a valuable role in research to better understand the horse’s physiological stress response, including both detrimental chronic stress and beneficial eustress, such as that experienced during controlled training challenges, playful social interactions and novel but manageable experiences that build confidence without overwhelming the horse and emotional conditions through HRV analysis [16,21]. Indeed, HR and HRV data can provide information on cardiac autonomic regulation, which is influenced by multiple factors including stress, pain, physical activity, low physical condition, lameness, among others, and may support welfare assessment [22]. HRM (Heart Rate Monitoring) technology utilised in

devices such as the Polar V800 and Actiheart 5, can provide inter-beat interval data. However, accuracy can be affected by movement artefacts, caused by sensor displacement relative to the skin. The Actiheart 5 records a full ECG waveform and allows manual correction of beat misidentifications, whereas the Polar V800 requires a 0.4 artefact correction to maximise data availability [23]. Sensors such as the Polar H10, which employ electrodes to capture data on the intervals between heartbeats, may also be used to monitor HRV in horses [16]. Similarly, PPG is a non-invasive approach that utilises a light source and a photodetector. The light source illuminates the skin tissue when the sensor activates and the photodetector captures reflected light from the

tissue, allowing it to detect changes in light absorption and thus blood volume alterations [19]. Wearable devices based on PPG technology have gained popularity in recent years since they can be produced with less expensive hardware rather than ECG [17]. The optical evaluation carried out by PPG devices requires two components: light-emitting diode (LED) and photodetector. Nevertheless, these elements must be placed closely to each other in contrast to ECG readings to prevent light dispersion, which would otherwise reduce the recorded signal [17]. Currently, there are several types of sensors available for measuring HR. An additional sensor that provides detailed data on the animal's health and performance is the Equimetre™, which is a device that assesses the horse's performance and assists in detecting any potential anomalies through heart rate monitoring [24,25]. It is a sensor that utilises a single lead electrocardiogram to monitor horses during exercise and has been shown to generate ECG recordings with fewer motion artefacts than those obtained from other devices [24]. Recent studies are developing smart textiles, such as chest strap with woven electrodes, designed to detect ECG signals and compared with the Televet™ telemetry system, which is considered the gold standard [26]. The electrodes provide good conductivity without the need to use invasive conductive gels [26]. Understanding the heart rate response to exercise allows trainers to optimise training programs so that horses are trained efficiently without overexertion, improving performance and avoiding injuries [27].

Other parameters that can be observed to improve horse welfare are those of respiratory rate and rhythm. Respiratory sensors support the diagnosis and monitoring of respiratory conditions using various technologies. Among these, millimeter-wave radar sensors are a recently developed method capable of detecting respiration with a contactless method, as demonstrated by [28] for detecting respiration in standing position and facilitating accuracy even in the presence of body movements. Among the main sensor models, forced oscillation technique (FOT) [29] represents a portable device that generates pressure oscillations using a servo-controlled ventilator. This technique allows for non-invasive measurement of respiratory resistance and reactance during spontaneous breathing in horses. In addition to FOT, piezoelectric sensors detect pressure variations across thorax to monitor subtle respiratory changes, while impedance sensors, such as those used by [30], measure lung ventilation based on changes in electrical conductivity. These are ideal in clinical assisted ventilation settings. Additionally, [31] contributed by creating a spirometry device with CO<sub>2</sub> flow sensors capable of managing large volumes of respiratory flow in anaesthetised horses. Furthermore, advanced diagnostic technologies such as electrical impedance tomography and impulse oscillation system allow detection of airway obstruction and analyse respiratory mechanics in detail, as reported by [32].

**3.1.1.1. Accuracy and reliability.** Many of the sensors assessing equine health parameters such as HR, HRV, respiration rate (RR), and ventilation of the lungs have been validated in various studies under different activity levels [16,18,20,22,24,25,28,29]. For example, validation of the Polar H10 ECG sensor was reported against telemetric ECG (Televet™ system), with comparable HR and HRV measurements during groundwork activity, with no significant differences for HR, SDNN, or RMSSD after artefact correction [16]. The Maxim integrated MAX30102 PPG sensor was reported as validated for HR monitoring against ECG-derived heart rate during rest and light movement, achieving 94 % accuracy in resting horses [18]. The 12-lead ECG system was used as a comparative benchmark alongside multiple wearable ECG devices during rest and submaximal exercise; while not explicitly labelled as a reference standard, it served as a methodological benchmark for arrhythmia and HRV analysis [20]. The Horse Wearable Systems (HWS) ECG was used in horses to assess HRV during rest and human-horse interaction, with high signal quality (< 0.15 % manual R-peak correction) sufficient for Kubios-based analysis, although no direct validation against an external gold standard was conducted in the same study [22].

The Polar V800 and Actiheart 5 ECG sensors were reported to provide reported to provide HRV estimates closely aligned with the Televet™ 100 ECG in horses at rest, during stationary conditions, achieving intraclass correlation coefficients (ICC) > 0.99 and HR bias < 0.2 bpm [23]. However, there are some limitations regarding Horsepal sensors in the measurement of heart rate as this device was not validated so far. The Equimetre™ sensor was reported as validated when compared to the Televet™ ECG system in two studies: the first confirming strong correlation for HR ( $r = 0.992$ ) and excellent concordance for HRV (Lin's concordance = 0.998) during high intensity exercise [25], and the second demonstrating high sensitivity (~ 95 %) and specificity (~ 99 %) in detecting arrhythmia during exercise [24,25]. The Skiin Equine sensor has also been reported as viable for HR and HRV tracking in horses at rest and during submaximal exercise, demonstrating strong agreement with the gold standard Televet™ ECG system, with a mean HR bias of 0.31 bpm and correlation coefficients above 0.87 for HRV parameters [26]. When monitoring the respiratory rate, satisfactory validation was reported for the MIMO radar, which showed strong correlation ( $r > 0.95$ ) and a mean absolute error of approximately 1 breath/min when compared with thermal imaging in standing horses [28]. The FOT device was also validated through a pilot study in both healthy and asthmatic horses, showing significant differentiation in respiratory mechanics, good tolerability and a maximum *in vitro* measurement error of 0.06 cmH<sub>2</sub>O/s/L for reactance [29]. As for the tidal volume, studies on the Electrical Impedance Tomography (EIT) sensor have demonstrated its utility in assessing pulmonary ventilation distribution during alveolar recruitment manoeuvres under anaesthesia, accurately detecting optimal ventilation with minimal overdistention between PEEP 17 and 12 cmH<sub>2</sub>O, alongside significant improvements in compliance and oxygenation [30]. In addition, a novel CO<sub>2</sub> flow-based spirometry system was reported to show limits of agreement within -1 % to +2 % *in vitro* and within ±10 % *in vivo* for clinically relevant tidal volumes in anaesthetised horses [31]. Finally, a review of IOS, EIT and spirometry studies supports their validated application in measuring airway resistance, reactance, ventilation, and perfusion in equine diagnostics [32]. Taken together, these observations map a range of these sensors' technologies that have been reported across multiple domains of the equine health and welfare assessment.

**3.1.1.2. Applicability.** In the analysed sensor stock, 54 % of the sensors (including Polar H10, Max30102 PPG, Polar V800, Actiheart 5, Equimetre™, Skiin Equine) were reported as suitable for field and controlled stable setting (e.g., prepared soil or barn) use [16,18,23,26,33]. In contrast, 46 % of the sensors, such as 12-lead ECG, HWS, EIT, MIMO radar, FOT, and CO<sub>2</sub> flow systems, were described as being used mainly in experimental settings (e.g., laboratories, stables and clinics) [20,22,28-32]. All sensors were noted to be sensitive to animal movement, leading to artefacts, and were affected by environmental conditions (e.g., humidity, sweating, sunlight), particularly for Polar H10, HWS, Equimetre™, EIT, Skiin Equine [16,22,24,25,30,32]. The MAX30102 PPG was reported as susceptible to interference with ambient light [18]. EIT and 12-lead ECG were noted to require skin preparation and conductive gel, to ensure optimal performance [16,20,30,32], on the contrary for the MAX30102 PPG which are without electrodes and conductive wires and consequently easier to apply [18]. Additional limiting factors included high cost [26,30,32] and rechargeable lithium battery with limited operational runtime (8-13 h); especially for Actiheart 5, that required frequent recharging [18,23]. Table 1 summarises the sensors cited in this subsection.

### 3.1.2. Temperature sensors

This paragraph includes 23 articles and reports 19 devices pertinent to this area.

Heat stress is a significant performance and welfare concern for a wide range of animals [13,14,34-36] including horses [37]. Indeed,

**Table 1**  
Summary of studies validating heart rate and respiratory rate monitoring technologies.

Sensor	Parameters monitored	Validation context and conditions	Applicability	Limitations	References
Polar H10 ECG	HR & HRV	Compared with Televet™ ECG during groundwork; no significant differences for HR, SDNN, or RMSSD after artifact correction	Applied for HR and HRV monitoring in short-term or controlled field applications; limited applicability for long-term continuous monitoring	Sensitive to environmental conditions and movement; requires skin preparation and use of gel	[16]
Maxim integrated MAX30102 PPG	HR	Compared with ECG at rest and light movement; 94 % accuracy in resting horses	Used for HR monitoring (94 % accuracy in resting horses), field usable (wireless); effective for real-time monitoring	Sensitive to environmental conditions (e.g., sunlight) and tail movements; limited battery autonomy	[18]
12-lead ECG	HR & HRV	Evaluated methodological benchmark alongside multiple wearable ECG devices during rest and submaximal exercise for arrhythmia and HRV analysis	Used for HR and HRV detection in experimental settings	Requires animal restraint; sensitive to movement and environmental electrical interactions; requires skin preparation, limited recording time	[20]
Horse Wearable Systems (HWS) ECG	HRV	Tested for HRV analysis (Kubios); high signal quality (<0.15 % manual R-peak correction); no direct validation against gold standard in same study	Reported as suitable for monitoring in specific experimental settings	Sensitive to humidity and movement	[22]
Polar V800 and Actiheart 5 ECG	HRV	Compared with Televet™ ECG during stationary rest (including dysrhythmic horses); ICC > 0.99 and HR bias < 0.2 bpm	Applied for HRV measurement in resting horses (both devices)	Sensitive to movement (both devices); does not provide full ECG trace (Polar V800); sensitivity to artefacts (v800 mostly); rechargeable lithium battery (13 h) (Actiheart 5 primarily); relatively economical (both devices)	[23]
Equimetre™	HR & HRV	Compared with Televet™ ECG in two studies: (1) strong HR correlation ( $r = 0.992$ ) and HRV concordance (Lin's = 0.998) during high-intensity exercise; (2) arrhythmia detection sensitivity ~95 %, specificity ~99 % during exercise	Used in experimental settings (e.g., research and monitoring); effective for HR and HRV measurement	Sensitive to movement and to environmental extreme conditions; ability to record only one lead; expensive	[24,25]
Skiin Equine Smart Textile	HR & HRV	Compared with Televet™ ECG during rest and submaximal exercise; mean HR bias 0.31 bpm; HR correlation $r = 0.9993$ ; HRV correlations $\geq 0.87$	Used for routine or prolonged low-intensity monitoring; useful for controlled stable setting (e.g., prepared soil or barn)	Sensitive to movement (especially during galloping); expensive; Sensitive to environmental conditions (e.g., humidity, wind)	[26]
MIMO radar	RR	Compared with thermal imaging in standing horses; $r > 0.95$ ; mean absolute error $\approx 1$ breath/min	Applied in experimental settings (e.g., laboratories, stables and clinics)	Sensitive to any body movement; expensive; complex positioning and configuration	[28]
FOT device	RR	Validated in vitro (max error: 0.06 cmH <sub>2</sub> O-s/L for reactance) and in pilot study with healthy and SEA horses	Reported as feasible in real-time monitoring	Manual data review required; complex calibration; depends on correct mask placement	[29]
EIT	Pulmonary ventilation	Compared during mechanical ventilation and recruitment manoeuvres; accurately detected optimal ventilation with minimal overdistention between PEEP 17–12 cmH <sub>2</sub> O; improved compliance and oxygenation	Used for advanced analysis of lung ventilation	Sensitive to movement and to changes in chest pressure or irregular breathing; expensive; complex positioning	[30]
CO2 flow sensor	Respiratory tidal volume	Compared with reference spirometry in anaesthetised horses; limits of agreement -1 % to +2 % in vitro; within $\pm 10$ % in vivo for clinically relevant tidal volumes	Applied in clinical and experimental settings	May cause discomfort (high respiratory resistance); sensitive to movement	[31]

equine athletes rely deeply on the thermoregulation mechanism [37]. Sustaining prolonged periods of intense competition can lead to the accumulation of excess metabolic heat in horses, which may reach potentially dangerously high core temperature [37,38]. While temperature sensors are useful for detecting critical increases in core body temperature, it should be noted that by the time these changes are measurable, the horse has already expended substantial metabolic energy to thermoregulate. For this reason, it is ideal to use temperature sensors in combination with other tools, such as heart rate monitors.

Temperature sensors used for core body temperature monitoring are generally thermocouples, thermistors [39], or infrared thermography (IRT). Thermistors are typically preferred over thermocouples due to their higher sensitivity, stability and minimal need for calibration [39]. Moreover, they are largely resistant to interference from external environmental factors such as fluid density or pressure. Although thermistors' response time is rapid, typically within seconds, the detection of core body temperature changes is determined by the device sampling intervals, which is often set at 10 minutes in rumen monitoring applications [39]. IRT sensors, by contrast, are typically used remotely and

have attracted the greatest interest in research on equines [40–43]. These devices can be used to detect temperature variations on the horse's skin, which is influenced by the underlying tissue metabolism and local blood circulation. Consequently, abnormal thermal patterns are the outcome of the alterations in physiological activity [44,42]. reported that a temperature difference of  $\geq 1.25^\circ\text{C}$  between contralateral limbs can indicate subclinical inflammation. These sensors have the advantage of not being intrusive to the animal and being able to measure the surface skin temperature of horse both before and after activity [37]. When there is an excess of inflammation, changes occur in the cutaneous blood flow and sweating patterns. A thermographic study on the thoracolumbar area in horses has been shown to detect heat distribution changes with a scoring system achieving 61.7 % sensitivity and 90.2 % specificity in detecting musculoskeletal stress in horses after leisure riding [45]. Several studies have shown that these sensors can be effectively used to assess fever or stress in horses by measuring ocular temperature [46–48]. Additionally, IRT readings have been correlated with blood lactate concentrations, a recognised and objective biochemical parameter for assessing a horse's physiological and

metabolic responses to exercise-induced stress, offering information on muscle workload, energy metabolism and thermoregulatory dynamics [49].

Thermocouples work through the Seebeck effect, which is the process of joining two dissimilar metal wires at both ends and exposing them to varying temperatures to produce a small thermoelectric current [50]. Investigations, such as those by [51–53], have used thermocouples by inserting them in different locations of the horse's body, including the pulmonary artery, rectum, and middle gluteal muscle. Furthermore, studies on cold treatment methods for equine digits have utilised thermocouples to monitor temperatures in the digital lamina and venous system, providing insights into the efficacy of different cooling procedures in treating inflammation and laminitis [52].

A telemetry-based temperature sensor can transmit data to a remote receiver through radio or electromagnetic signals when placed inside an animal. Similarly, horses' core body temperature can be monitored by ingesting a gastrointestinal pill that continually measures temperature during both rest and physical activity [54]. In field conditions, the transmission range of the gastrointestinal pill has been reported to be 1 m, recording data at ~5-15 seconds intervals [54]. In vivo recording durations typically extends around 5 days, permitting monitoring under grazing conditions, as long as the horse wears the receiver. However, the system is not intended for long range direct transmission [54]. This pill can be paired with an Equivital Electronic Sensor Module (SEM). The SEM is positioned in a modified belt that fits firmly around the horse's ventral thorax, permitting accurate, reliable and non-invasive monitoring of core body temperature and other physiological parameters throughout activity and recovery [55].

Another innovative method involves implanted microchips with temperature monitoring capabilities [56,57]. These microchips can help monitor a horse's body temperature during and after activity [56]. They are especially effective in monitoring horses over extended periods [58]. In the study of [58], the thermal sensing microchips were implanted and then used for daily monitoring over 17 to 23 days in ponies and 19 days in Quarter Horses without issues. However, their accuracy is influenced by ambient temperature, with performance being optimal when temperatures exceed 15.6°C [58]. Using this technology, devices such as the Bio-Thermo microchip provide real-time temperature information that may be accessed through a handheld scanner.

Although temperature sensors are not widely documented in the published peer-review literature, several reliable models are available on the market. Due to their user-friendliness, Horsepal and VetTrue system are two noteworthy sensors available on the market that have gained considerable attention. Horsepal, developed in Ireland, is a smart sensor that can be attached to the horse's girth or blanket. It keeps track of and logs the temperature frequently, providing real-time information to the owner's smartphone through a specialised app. The VetTrue system, on the other hand, takes advantage of a non-invasive, wearable device that is attached to the horse's body, under the tail, to measure its temperature continuously without causing pain to the animal. The VetTrue system tends to record temperatures that are typically around 0.5°C to 1.0°C lower than the horse's rectal temperature.

**3.1.2.1. Accuracy and reliability.** The efficiency and effectiveness of numerous sensors in animals, including IRT cameras, thermocouples, telemetered sensors, and implantable microchips, have been described in several studies, with many devices evaluated against recognised gold standards or supported by consistent physiological correlations [40,42, 45,46,48,49]. IRT technologies have been applied to the thoracolumbar region and body surface using devices such as the FLIR Thermo CAM E25, with validation in some studies through physiological changes assessed by texture and pattern analysis, although no quantitative accuracy metrics were reported [40,45]. In another study, IRT using the same device showed strong correlations with blood lactate concentration after exercise ( $\rho = 0.83\text{--}0.85$ ) [49]. The VarioCam HD Research 775

infrared camera demonstrated a bias of 0.21°C with limits of agreement (LoA) from  $-0.65^\circ\text{C}$  to  $1.07^\circ\text{C}$  when calibrated against a blackbody source [41], while the Fluke PTi120 Pocket Thermal Imager [48] has been applied in field conditions without direct quantitative validation. Devices such as the FLIR ThermoCAM EX320, FLIR T420 and FLIR ThermoCam S60 have been applied for ocular monitoring. Thermographic eye temperature (IRT) was compared with rectal temperature and implanted thermal microchip measurements, with a reported sensitivity of 74.6 % and specificity of 92.3 % for detecting febrile individuals ( $> 38.6^\circ\text{C}$ ) when using the maximum daily eye temperature per animal [43]. In horses, IRT measurement at the medial canthus was compared with rectal temperature, with a significant positive correlation ( $p < 0.05$ ) and highest accuracy obtained using the smallest region of interest ( $2 \times 2$  pixels) [44]. In dairy cattle, eye temperature measured with IRT was compared to core body temperature, although no quantitative accuracy metrics were reported; changes were detected after catheterization but not after exogenous HPA stimulation [47]. The NEC Avio TV5500 has been used to measure lacrimal caruncle temperature in horses, detecting significant increases after a novel object test ( $p < 0.01$ ) compared to baseline; however, it was not directly evaluated against a gold standard temperature measurement in the same study [46].

Telethermometry or thermocouples have been evaluated for internal temperature measurement. Physitemp copper-constantan sensors showed strong agreement with pulmonary artery and rectal temperatures [51]. Tissue-implantable thermocouples were used to measure laminar and venous temperatures in horses and have been shown to effectively track these temperatures, with the placement protocol described in previous work [53] and successfully applied in other studies [52,53]. In another study, thermocouples attached to Equivital sensors were tested against a certified RTD (bias  $-0.14^\circ\text{C}$  in vitro) and a rectal probe (bias  $+0.27^\circ\text{C}$  in vivo; accuracy  $\pm 0.1^\circ\text{C}$ ) during rest, exercise, and recovery [54,55].

Microchip-based technologies, such as the PTSM LifeChip® with Bio-Thermo™ technology, have been compared with central venous temperature (TCV) in multiple anatomical locations, including the pectoral, gluteal, and splenius muscles, and the nuchal ligament, with post-exercise correlations ranging from  $r = 0.85$  to  $0.92$  ( $p < 0.05$ ) [56]. The Allflex identification microchip has been evaluated against calibrated rectal thermometers, showing a mean bias of  $-0.18^\circ\text{C}$  (LoA:  $0.88$  to  $+0.53^\circ\text{C}$ ) [57]. Preliminary screening of PTSM LifeChip® placement between the poll and withers reported feasibility, with rectal temperature as the reference and fever-detection sensitivity up to 87.4 % in warm ambient conditions [58]. Collectively, these studies map the reliability of microchip-based temperature monitoring across diverse anatomical sites in horses.

**3.1.2.2. Applicability.** The need for continuous monitoring of equine temperature has led to the adoption of advanced technologies. Among the previously mentioned technologies, the IRT sensors, such as the Fluke PTi120 Pocket model ( $-20$  to  $400^\circ\text{C}$ ) and the VarioCam HD Research 775 ( $-20$  to  $1200^\circ\text{C}$ ), were reported as suitable for the measurement of wide temperature ranges [41,48]. However, authors report that the performance of these sensors is influenced by environmental factors (e.g., humidity and temperature), limiting their use to experimental settings [40,41,43–47]. Similarly, thermocouple systems have also been reported as applicable primarily in experimental settings with the fundamental limitation of being particularly invasive and difficult to manage [51–53]. In contrast, implantable microchip systems, such as the PTSM LifeChip® ( $32^\circ\text{C}$  -  $43^\circ\text{C}$ ) and Allflex ( $33^\circ\text{C}$  -  $45^\circ\text{C}$ ), were reported to have a greater resistance to changes in environmental factors. In addition, although their detection range is narrower their high cost is mainly justified by their operational lifespan [56–58]. Table 2 presents an overview of the sensors cited in this subsection.

**Table 2**  
Summary of studies validating temperature monitoring technologies.

Sensor	Parameters monitored	Validation context and conditions	Applicability	Limitations	References
IRT: FLIR Therma CAM E25	Thoracolumbar Region	Compared with physiological changes using texture analysis; no quantitative accuracy reported	Used for individual monitoring in experimental settings	Sensitive to environmental conditions (e.g., humidity, temperature), limited battery capacity (2-3 h); long charging times	[40,45]
IRT: VarioCam HD Research 775 infrared camera	Body surface	Calibrated against blackbody source (bias 0.21°C; LoA: 0.65°C to +1.07°C)	Reported as suitable for individual monitoring in experimental setting	Sensitive to environmental factors (e.g., humidity, sunlight, wind); expensive; complex data management; difficult to transport	[41]
IRT: FLIR ThermaCAM EX320	Eye	Compared with rectal temperature; sensitivity 74.6 %, specificity 92.3 % for detecting fever (> 38.6°C)	Reported as appropriate for individual monitoring in experimental setting	Sensitive to environmental factors, regular calibration needed; requires specific software for data analysis; expensive	[43]
IRT: FLIR T420 infrared radiation camera	Eye	Compared with rectal temperature; highest accuracy with 2 × 2 px ROI	Applied for individual monitoring in experimental setting	Sensitive to environmental factors; expensive; complex data interpretation; needs regular calibration	[44]
IRT: NEC Avio TVS500	Lacrimal caruncle	Tested in fear tests; no direct quantitative accuracy vs. gold standard	Used for individual monitoring in experimental setting; effective for monitoring animal welfare through measuring lacrimal caruncle temperature	Sensitive to environmental factors; needs trained personnel, no continuous monitoring	[46]
IRT: FLIR ThermaCam S60	Eye	Tested in stress response experiment with eye temperature monitoring	Reported as suitable for individual monitoring in experimental setting; ideal to measure stress levels	Sensitive to environmental factors; complex data interpretation; no continuous monitoring	[47]
IRT: Fluke PT1120 Pocket Thermal Imager	Body surface (vulva, eyes, muzzle, and flanks)	Compared using body surface gradients correlated with pregnancy status; no quantitative accuracy vs. gold standard	Used for individual monitoring in experimental setting	Sensitive to environmental factors; requires trained personnel; no continuous monitoring	[48]
IRT: FLIR Therma CAM E25	Body surface	Compared with blood lactate levels during exercise ( $\rho = 0.83-0.85$ )	Reported as applicable for individual monitoring in experimental setting	Sensitive to environmental conditions; requires specific software for data processing; no continuous monitoring	[49]
Thermocouple: Physitemp copper-constantan	Pulmonary artery	Compared with reference pulmonary temperature probes	Reported as feasible for measuring internal body temperature during intense exercise	Invasive; requires trained personnel	[51]
Thermocouple: Physitemp copper-constantan	Rectal	Compared with certified RTD in water baths	Used for measuring internal body temperature during intense exercise	Invasive; requires trained personnel	
Thermocouple: Physitemp model MT-23	Muscle	No validation reported	Applied in experimental setting	Invasive, requires regular calibration and maintenance; sterility required; possible discomfort	
Thermocouple: Physitemp model SST-1	Skin	No validation reported	Reported as appropriate for experimental setting	Invasive; sensitive to environmental factors; requires regular calibration and maintenance; difficult to keep in place	
Thermocouple: Tissue-implantable	Digital laminar and venous	Tested via digital vein/laminar cooling during cryotherapy	Used for clinical or experimental settings	Invasive (local anaesthesia required); needs sterility; no continuous monitoring; difficult removal	[52]
Thermocouple	Skin and lamellar	Tested using skin/lamellar response under clinical models	Applied for clinical and experimental settings under controlled conditions	Invasive; requires sterility; expensive; needs experienced personnel	[53]
Telemeter-based: Paired with Equivital sensor	GI	Compared with certified RTD (bias -0.14°C in vitro) and rectal probe (bias +0.27°C in vivo; accuracy ±0.1°C)	Reported as applicable for detecting temperature during training, competition and recovery	Sensitive to extreme environmental factors or prolonged sun exposure; needs compatible reader for data collection; expensive installation	[54,55]
Microchip: PTSM LifeChip® with Biothermo™ microchip	Body temperature (Nuchal ligament, splenius muscle, gluteal muscle, and pectoral muscle)	Compared with central venous temperature; post-exercise correlations $r = 0.85-0.92$ ( $p < 0.05$ )	Used for continuous temperature monitoring	Sensitive to environmental factors; accuracy dependent on implantation site; invasive (local anaesthesia required); significant initial cost	[56]
Microchip: Allflex identification microchip equipped with a temperature sensor implanted in neckline	Body temperature	Compared with calibrated rectal thermometer; (bias -0.18°C; LoA: 0.88 to +0.53°C)	Applied for continuous temperature monitoring	Accuracy affected by environmental factors; significant initial cost	[57]
Microchip: PTSM LifeChip® with Biothermo™ microchip	Body temperature (nuchal ligament, halfway between the poll and withers)	Compared with rectal temperature for fever detection; sensitivity up to 87.4 % in warm conditions	Reported as feasible for indoor or outdoor environments and continuous monitoring	Sensitive to environmental factors (< 15.6°C temperature underestimation); needs trained personnel; temperature duration dependent on environmental factors; requires surgical for implantation	[58]

### 3.1.3. Accelerometers

In this section, 20 articles were reviewed. We identified 12 accelerometers applicable to this field.

Accelerometers are widely used in equine veterinary research [59–62] and have become increasingly popular in recent years. These sensors monitor the acceleration forces operating on the horse's body, which may be analysed to evaluate many aspects of movement and behaviour. Through the use of this data, it is possible to achieve a deeper understanding of equine activity using a machine learning-based approach [63,64]. The application of accelerometers in equine science has provided important insights into the monitoring of locomotor activity [65–68]. The research conducted by [65] compared data acquired from an accelerometer to data collected from a standard pedometer. The study included 20 horses of various breeds, and the results highlighted that the accelerometer was highly successful in distinguishing between different gaits based on the vertical leg movement, with no overlap in acceleration value ranges for different gaits. Furthermore, the research indicated that the MSR145 accelerometer is a valid alternative to standard pedometers for monitoring both locomotor activity and resting behaviour in horses. Indeed, these sensors are frequently integrated into wearable devices, allowing continuous and non-invasive monitoring of horse gait during different activities and in detecting and quantifying lameness by monitoring asymmetries in the horse's movement [67]. One common example is the EquiSense Motion® sensors, which combines accelerometric and gyroscope technology to provide detailed analysis of gait, stride length, and movement patterns [33]. While accelerometers measure linear acceleration, a gyroscope measures angular velocity. This rotational data improves the ability to distinguish between different gaits where the body rotates as well as moves linearly. When integrated with accelerometer data, gyroscopic measurement contributes to a more complete representation of movement, which improves the accuracy of activity classification and the detection of minor asymmetries or deviations in movements [69]. The application of accelerometers in the equestrian sector is extensive. For training purposes, accelerometers can measure the intensity and duration of activity during training, allowing trainers to create more effective and personalised training protocols [69, 70]. The capacity to automatically recognise and categorise complicated dressage and jumping activities can considerably improve training and monitoring methods, allowing for improved assessment of horse endurance and performance [69]. Accelerometers monitor changes in the horse's motion in three axes: forward-backward, vertical, and lateral. Accelerometer data, when combined with GPS measurements, can be processed using proprietary correction algorithms to achieve positional accuracy of about 10 cm, even under dynamic conditions and vertical oscillations [70]. The system calculates stride length, duration and count based on the time between hoof strikes and the duration of the horse's flight phase [70].

In the context of health monitoring, accelerometers may detect minor changes in horse's gait and posture, allowing for early detection of lameness [66,71,72]. Crecan et al. [71] have developed a device, named the Lameness Detector 0.1, which has four sensors strategically placed on the horse's legs. Using accelerometers that track the motion of the horse's legs in three dimensions, the sensors capture dynamic acceleration during key phases of the strides, such as hoof-off, the swing phase, and hoof-on, and calculating the number of accelerations throughout each stride. Accelerometric data can help early detect certain pathologies, such as colic, through the use of data processed by machine learning algorithm, allowing for prompt intervention before the condition advanced to a critical stage [73]. The study of [73] demonstrated that a machine learning algorithm classified pain-related behaviours with over 99 % accuracy and detected colic on average of 20 minutes before the pain peak and 4 minutes prior to onset. Moreover, the Equinosis Q system uses accelerometers located on the horse's body and is sensitive enough to measure movements differences as small as a few millimeters [74]. The system compares the horse's right and left movements, identifying any discrepancies. Based on the data collected,

the software assigns a symmetry score to quantify the detected differences [74]. This system is also used to detect whether asymmetries are present from a young age, by precisely measuring the differences in movement between the right and left strides, allowing for early detection and monitoring of potential gait irregularities [75]. Moreover, accelerometers can help monitor horse welfare by classifying certain behaviours. They can detect variability in activity count that may show behavioural patterns associated with signs of discomfort or stereotypies, suggesting welfare concerns. For example, devices like HoofStep®, which contain an accelerometer, gyroscope, and GPS, are able to monitor horse activities and classify them into one of four categories: "feeding", "resting", "active", and "highly active" [76]. In this study, which involved geriatric and orthopaedically challenged horses, deviations from expected time budgets for feeding (~42 %), resting (~39 %) and movement (~19 %) were connected to management conditions such as limited access to forage and high stocking density. Meanwhile, horses housed in greater environmental enrichment showed time budgets more consistent with indicators of positive welfare. Activity peaks observed just before scheduled feeding times in horses kept on restricted diets and non-edible bedding likely reflect anticipatory stress response [76]. Additionally, accelerometers such as HOB0 Pendant® G Data Logger can be used to record data at customisable time intervals, allowing the monitoring of equine postures, including standing, lying positions and to identify variations in lying postures, such as sternal or lateral recumbency [77].

**3.1.3.1. Accuracy and reliability.** The movement, health, and behavioural patterns of equines can be monitored using various sensor technologies, several of which have been evaluated against gold standards with reported quantitative outcomes. The GT3-X+ triaxial accelerometer has been tested for accurate determination of gait by comparing accelerometer output to direct video observation of horses at rest, walking, trotting, and cantering [68]. The study demonstrated sensitivity and specificity values exceeding 96 % across gaits (e.g., 100 % specificity for rest, 96.7 % sensitivity for trotting), confirming its utility for measuring physical activity levels in horses [68]. The MSR145 sensor has also been reported in distinguishing between horse movements, with evaluation against a pedometer and definition of distinct acceleration value ranges that did not overlap between gaits, supporting its high precision [65]. To determine levels of physical activity engagement, inertial measurement units (IMUs) were described as showing comparable or superior accuracy to force plates and optical motion capture systems, although the specific devices used were not always identified [67]. The Equisense Motion S®, another IMU-based device, was reported with repeatability values up to 0.72 for elevation traits and a positive correlation with judge evaluations, supporting its use in training and gait quality assessment [33]. The EquiSense Motion S®, another IMU-based device, was reported with repeatability values up to 0.72 for elevation traits and a positive correlation with judge evaluations, supporting its use in training and gait quality assessment [33]. The Axivity AX6 6-Axis logging device was applied in training scenarios for jumping and dressage, with neural networks yielding 96-100 % classification accuracy for training movements [69]. In addition, this device has been used to detect early signs of colic, with a validated algorithm achieving a detection accuracy of 91.2 % and a colic severity classification accuracy of 93.8 % [73]. The INSECO IMU (for indoor use) and Noraxon MPU-9250 (for outdoor use) have been applied to evaluate lameness and gait, using machine learning techniques, including RNN-LTSM and pose estimation models, with lameness detection accuracies up to 95 % and joint angle predictions errors under 10° [72]. The Equinosis Q system was compared with other IMU-based systems and AI tools such as Sleip AI and Equimoves®, showing agreement in asymmetry classification and stride analysis [74,75]. To assess time budgets and activity counts, Hoofstep® has been reported as applied in various husbandry environments, highlighting its utility for welfare studies

although quantitative validation metrics were not explicitly reported [76]. Lastly, the HOBOPendant® G Data Logger has been compared with video-based observations, achieving predictive accuracy over 98 % in detecting equine postures such as sternal and lateral recumbency [77]. These studies, collectively, highlight the importance of wearable sensory technologies in advancing the precision monitoring of equine health, behaviour, and performance.

**3.1.3.2. Applicability.** The applicability of accelerometer sensors reported in the literature is extensive. In fact, sensors such as MSR145, Equisense Motion S®, Equinosis Q and Hoofstep® were described as feasible in outdoor environments, with data collection possible even under humid or rainy conditions [33,68,74–76]. In fact, sensors such as MSR145, EquiSense Motion S®, Equinosis Q and Hoofstep® were described as feasible in outdoor environments, with data collection possible even under humid or rainy conditions [33,68,74–76]. In contrast, devices such as the GT3-X+ and the Apple Watch Series 4 were applied mainly in moderately controlled scenarios, limiting their

broader use [65,67]. However, the operational runtime of the device is dependent on the selected sampling frequency that precludes continuous monitoring as reported for the Apple Watch Series 4, the EquiSense Motion S®, the Axivity AX6, and the HOBOPendant® [33,65,69,73,77]. In contrast, sensors such as the MSR145 and GT3-X+ have been noted for greater autonomy, making them suitable for extended periods without interruption [67,68]. Another important aspect reported concerns the complexity in data management. In particular, devices such as the Axivity AX6, Equinosis Q, INSENCO IMU (indoor) and Noraxon MPU-9250 (outdoor) generated large volumes of raw data that could only be processed with advanced software limiting their practicality in field applications [69,72,73]. Table 3 summarises the sensors cited in this subsection.

#### 3.1.4. GPS Devices

A total of 10 articles were analysed in this paragraph, from which we reported 4 devices relevant to this specific area of application.

In recent years, GPS devices have become more popular in equestrian monitoring. Wearable GPS sensors utilise satellite signals to identify the

**Table 3**  
Summary of studies validating accelerometer technologies.

Sensor	Parameters monitored	Validation context and conditions	Applicability	Limitations	References
GT3-X+	Gait determination	Compared with video observation; Sensitivity and specificity > 96 % across gaits	Applied for field and clinical settings for pre- and post-treatment monitoring	Sensitive to extreme environmental conditions (e.g. heavy precipitation, temperature >35-45 or <10, high % of humidity); manual data transfer via USB	[68]
MSR145	Horse Movement Analysis	Compared with ALT pedometer and acceleration ranges for stand/walk/trot/gallop; non-overlapping gait ranges confirmed high accuracy	Reported as feasible for short-term monitoring in clinical and field settings	Sensitive to extreme environmental conditions (e.g. heavy precipitation, temperature >35-45 or <10, high % of humidity); limited operational runtime; expensive	[65]
GT3-X+	Physical activity	Compared with video observation; machine learning models achieved >97 % classification accuracy	Used in experimental setting	Sensitive to environment conditions; data management complexity; expensive	[67]
EquiSense Motion S®	Gait detection	Tested for repeatability and correlation with judge evaluations; repeatability up to 0.72	Reported as useful for training, clinical rehabilitation and biomechanical studies.	Sensitive to extreme environmental conditions (e.g. heavy precipitation, temperature >35-45 or <10, high % of humidity); limited operational runtime; discomfort from prolonged use; expensive; limited real-time data	[33]
Axivity AX6 6-Axis Logging Device	Dressage and jumping training movements	Tested using neural networks; 96-100 % classification accuracy for movements	Applied for performance monitoring in experimental setting	Complex data management; expensive; moderate sensitivity to environmental factors	[69]
INSENCO IMU (indoor) & Noraxon MPU-9250 (outdoor)	Lameness and gait detection	Tested using RNN-LSTM and pose estimation; 95 % lameness detection accuracy, joint angle errors <10°	Reported as feasible for behavioural monitoring	Sensitive to vibrations and irregular movements; requires significant data storage	[72]
Axivity AX6 6-Axis Logging Device	Early colic detection	Compared through experimental induction; algorithm accuracy 91.2 % (detection), 93.8 % (severity classification)	Reported as suitable for experimental setting; possible field use with battery upgrade	Complex data management; expensive; moderate sensitivity to environmental factors; limited operational runtime	[73]
Equinosis Q with Lameness Locator® & Equimoves®	Lameness and gait detection	Compared with other IMU systems and AI tools; strong agreement on asymmetry detection	Used in clinical and field settings	Sensitive to extreme environmental conditions (e.g. heavy precipitation, temperature >35-45 or <10, high % of humidity); complex data management; expensive; limited operational runtime	[74]
Equinosis Q with Lameness Locator®	Motion analysis	Tested through field comparison studies with IMU systems and subjective evaluation	Applied in clinical and field settings	Sensitive to environmental conditions (e.g. heavy precipitation, temperature > 35-45°C or < 10°C, high % of humidity); complex data management; expensive; limited operational runtime	[75]
Hoofstep®	Time Budgets and Activity Counts	Tested through welfare studies; specific quantitative metrics not detailed	Reported as suitable for experimental setting and open environments (e.g. paddocks, pastures, stabling). Reported as suitable for experimental setting and open environments (e.g., paddocks, pastures, stabling).	Sensitive to extreme environmental conditions (e.g. heavy precipitation, temperature > 35-45°C or < 10°C, high % of humidity); limited operational runtime; requires stable connection	[76]
HOBOPendant® G Data Logger	Postures	Tested through video-based comparison; >98 % predictive accuracy for recumbency	Applied in behaviour monitoring (e.g., resting) inside stalls	Sensitive to humidity; limited operational runtime; no real-time monitoring	[77]

spatial location of horses [78,79] and calculate the total distance covered [70,80,81]. The main feature of these sensors is to monitor the horse's movements, speed and parameters related to the animal's overall health. For instance, these systems are frequently combined with additional sensors, such as photoplethysmography (PPG) technology to monitor heart rate and accelerometers to measure physical activity [82]. In this study, a PA1010D Mini-GPS sensor with a 10 Hz update rate is utilised. The GPS data is mostly used to observe how horses move within the pasture, tracking their paths and identifying areas where they spend more time [82]. By correlating location data with physiological responses, the system can identify possible stressors in the environment, such as proximity to feeding stations. Similarly, the idea of combining GPS systems with IMUs has been investigated to overcome the limitations of conventional sensors [83]. By developing machine learning models from data collected across various gaits such as walking, trotting, pacing, it is possible to have a highly accurate estimate of speed regardless of where the IMU is positioned and the type of gait [83]. Indeed, in the study of [83], models based on random forest method using data from all IMU positions reached a root mean square error (RMSE) of 0.25 m/s and a mean absolute error (MAE) of 0.14 m/s

GPS systems may be quite useful for health monitoring. Indeed, stride rate data from GPS can provide information regarding potential musculoskeletal injuries in racehorses; a decrease in speed or stride length may be associated with this type of injury [84]. Timely measurements of these parameters via GPS systems can help recognise horses at risk of injury [85]. A recent GPS sensor that has been cited in literature is the Alogo Move Pro. This device validates the GPS system and accelerometer data, using an Extended Kalman Filter (EKF) to guarantee more accurate position and tracking speed over time. This sensor was validated against a gold-standard optical motion capture (OMC) system, which showed relative accuracy ranging from 5.5 % to 29.2 % for jump parameters and 10.5 % to 20.7 % for stride measures [86]. Despite occasional GPS signal loss in closed environments, the Alogo Move Pro proved to be a trustworthy instrument for real-world applications [86]. GPS sensors can also be incorporated into electronic collars with a standard GNSS (Global Navigation Satellite System) module for accurate tracking of animal locations [11]. When integrated into a modular collar, the GNSS module supports flexible design configurations that can adapt to different species and telemetry needs, allowing both animal welfare and data collection efficiency.

**3.1.4.1. Accuracy and reliability.** Several studies have reported on the performance of various GPS sensors designed for tracking and monitoring animal movement. The Mini GPS PA1010D sensor, integrated into a multifunctional wearable IoT device for horses, was evaluated for geolocation tracking, achieving a positional accuracy of <3 m. Additionally, the device's heart rate sensor (MAX30102 PPG) was compared with stethoscope auscultation, with a reported accuracy of 95 % across eight subjects [82]. In terms of speed estimation, the VBox Sport from Racelogic was assessed in validation studies; stride frequency values derived from GPS speed fluctuations were compared with IMU pitch data (Xsens DOT), with bias of 0.0032 Hz and a sample-by-sample precision of  $\pm 0.027$  Hz, supporting its suitability for injury risk studies [85]. Gait detection and analysis in animals was reported using an Alogo Move Pro device from Alogo Swiss Technology, validated against a traditional optical motion capture system, with an accuracy for stride and jump segments ranging from 5.5 to 29.2 % and precision values of 2.8-18.2 %, corroborating its efficacy [86]. Although the GNSS module, was not directly validated against a gold-standard GPS system, it was designed using a rigorous animal-centred engineering approach and integrated into a modular collar with demonstrated field performance, supporting its potential utility in livestock applications [11]. These studies describe the reported contributions of GPS sensors to the study of animal movement and behaviour.

**3.1.4.2. Applicability.** The GPS sensors analysed were reported with different applications and limitations depending on their context of use. Some devices such as the PA1010D Mini GPS and the GNSS module were noted to be highly adaptable for monitoring groups of horses in both clinical and field settings [11,82]. These devices required the integration of LoRa and Bluetooth systems to allow real-time data transmission over long distances. In contrast, the evaluation of the individual performance during training, particularly in galloping and jumping competitions, was reported by the Vbox Sport devices [85] and the Alogo Move Pro [86] except for the lack of real-time monitoring capabilities. Across all sensors, limitations were reported, including relatively short operational durations before recharging or battery replacement and sensitivity to environmental factors, such as obstacles and extreme weather conditions, which disrupted signal and data collection. Notably, the GNSS sensor featured innovative design elements, including airtight, lightweight materials and a quick release (drop-off) system, supporting its applicability in different environments [11]. Table 4 presents an overview of the sensors cited in this subsection.

## 3.2. Non-wearable technology

### 3.2.1. Microphones

In this section, 6 studies were examined. This analysis led to the identification of 3 microphones relevant to recording equine sound data.

Microphone-based technologies provide a non-invasive method to monitor welfare of horses. Equine vocalisations, such as snorting or neighing, may communicate both positive and negative emotional states [87]. If external noises are not adequately controlled, they can induce anxiety in horses, which can lead to physical injuries such as escape attempts or accidents with fences [88]. Exposure to sound can considerably alter HR in horses, with stress levels increasing when the sound source is close by [89]. To prevent this from happening, environmental microphones can play an important role, providing immediate feedback on external noise levels. Although the use of microphones in equine research is not extensively covered in the literature, some studies have utilised them incorporated inside micro-cameras to detect various acoustic occurrences such as biting, chewing or external disturbances [90]. In this investigation, the microphone recorded sound within the 0-18 kHz range, and the data was pre-processed to remove external noise [90]. Common alternatives include unidirectional microphones for analysing respiratory sounds in horses with recurrent laryngeal neuropathy (RLN). In [91]'s study, a Sennheiser E608 directional cardioid microphone, placed near the right nostril through an endoscope, is used to record respiratory noise during exercise. The microphone is connected to a Tascam DR40 digital recorder, examining sound energy in different frequencies. Another system described in the literature is the ThoraView®, an innovative technology designed to dynamically visualise lung ventilation [92]. This system uses an array of 30 microphones placed on a back pad, recording respiratory sounds to map ventilated and non-ventilated areas in the lungs of animals.

**3.2.1.1. Accuracy and reliability.** Several sensor technologies have been tested with respect to the monitoring of selected physiological or behavioural parameters of animals. The LK-SC100B micro-camera, manufactured by LKSUMPT and integrated with a microphone (0-18 kHz), was evaluated for the identification and distinction of bite and chew events in horses using a deep learning model trained on manually annotated video/audio recordings as the gold standard. The system achieved 88.64 % accuracy for bite identification and 94.13 % for chew identification, demonstrating its effectiveness for monitoring grazing behaviour [90]. The E608 unidirectional cardioid microphone, produced by Sennheiser UK Ltd., was applied for the respiration noise monitoring during overground endoscopy, though no formal validation research has been conducted for it, so far [91]. The E608 unidirectional cardioid microphone, produced by Sennheiser UK Ltd., was applied for

**Table 4**  
Summary of studies validating GPS technologies.

Sensor	Parameters monitored	Validation context and conditions	Applicability	Limitations	References
Mini GPS PA1010D (Adafruit Industries LLC)	Location tracking	Not validated against gold-standard GPS; positional accuracy < 3 m; performance supported by field deployment	Reported as feasible for monitoring grazing herds; effective for behavioural monitoring and welfare assessment	Limited transmission distance (< 3 m); sensitive to environmental obstacles; limited storage capacity	[82]
VBox Sport (Racelogic)	Speed estimation	Compared with IMU-derived stride frequency (Xsens DOT); bias= 0.0032 Hz; precision= 0.027 Hz	Reported as suitable for monitoring during training; performance improvement and effective for monitoring animal welfare	Requires good satellite coverage; lacks real-time analysis; limited autonomy (6 h)	[85]
Alogo Move Pro (Alogo Swiss Technology)	Gait detection	Compared with optical motion capture system (Qualisys); accuracy for stride/jump segments= 5.5-29.2 %; precision= 2.8-18.2 %	Used for monitoring during training; Useful for performance improvement in the field	Prone to GPS signal loss (e.g., under heavy metal structures); no real-time monitoring (memory store 10 h ride data); limited transmission distance (10 m), rechargeable lithium battery (14 h)	[86]
GNSS module	Tracking	Not validated against a GPS gold standard; field-tested in livestock applications with reported usability but without positional accuracy data	Applied for monitoring individuals and groups; useful for behavioural and welfare monitoring in the field	Complex locking system; unsuitable for extreme weather conditions (e.g. heavy precipitation, temperature >35-45°C or <10°C, high % of humidity); external power is required, limited transmission distance (< 3 m)	[11]

the respiration-noise monitoring during overground endoscopy, though no formal validation research has been conducted for it, so far [91]. The Thora Tech GmbH's ThoraView was tested in piglets against CT and MRI imaging for identifying ventilated and non-ventilated lung areas, and has shown a significant discrimination ( $p < 0.01$ ) between conditions, its application in equine species remains untested. Nonetheless, its underlying acoustic technology presents a promising direction for non-invasive equine respiratory monitoring [92]. The illustrated studies illustrate the varying validation approaches and reported accuracy outcomes of sensor technologies regarding horse health monitoring applications.

**3.2.1.2. Applicability.** Microphone sensors have been described in the literature as versatile tools for monitoring physical and behavioural parameters in animals. Their versatility lies in the possibility of their integration with other instruments such as headstocks (LK-SC100B), endoscopes (E608), and dorsal skin positioning devices (ThoraView) [90–92]. However, limitations include the LK-SC100B device's difficulty in the differentiation between prehension and chewing sounds [90]. In addition [92], and [91] pointed out that sound analysis is complex in the presence of multiple dynamic anomalies and that artefact recognition remains an unresolved problem [91,92]. Table 5 summarises the sensors cited in this subsection.

**Table 5**  
Summary of studies validating microphone technologies.

Sensor	Parameters monitored	Validation context and conditions	Applicability	Limitations	References
LK-SC100B micro-camera (LKSUMPT)	Detect and distinguish bite and chew events	Compared with synchronised video/audio recordings; achieved 88.64 % accuracy for bone identification and 94.13 % for chew identification	Applied for monitoring the grazing and feeding behaviour of individual horses; effective for real-time monitoring	Difficulty discriminating sounds; significant data storage and processing systems required.	[90]
E608 unidirectional cardioid microphone (Sennheiser UK Ltd)	Respiratory sound	Not yet validated; applied in clinical studies; used for formant-based acoustic analysis	Reported as suitable for monitoring individual horses in controlled clinical settings; effective for monitoring respiratory sounds in real time	Challenges in sound analysis caused by dynamic abnormalities; atmospheric sensitivity (e.g., wind, rain); continuous power supply required	[91]
ThoraView (Thora Tech GmbH)	Lung Ventilation	Compared with CT and MRI imaging; significant discrimination between ventilated and non-ventilated areas ( $p < 0.01$ ); no equine-specific validation to date	Described as feasible for monitoring individual subjects in specific clinical settings; effective for real-time monitoring of pulmonary ventilation and detecting unventilated lung areas.	Complex setup; sensitive to motion and weather; high cost.	[92]

### 3.2.2. Behaviour recognition through computer vision

In this final paragraph, we analysed 19 articles from which we identified 6 models and 5 datasets.

Equine monitoring has witnessed an increase in the use of computer vision and machine learning techniques to recognise certain horse behaviours [93]. Through the use of deep learning systems, it is possible to observe and interpret a horse's behaviour by analysing visual data captured by cameras [63]. The possibility to recognise certain behaviours visually, indirectly allows to identify the animal's emotions and issues [94–97].

Reconstructing and extracting properties from images, such as forms, textures, densities and distances, is the primary concern of computer vision, through the development of artificial systems that address visual issues using image processing and analysis techniques [98]. These cameras continuously capture video data, which provides a sufficiently large collection of samples required for training artificial neural networks. MS COCO is one of the largest object recognition datasets available today which includes animal classification like horses [99] (labelled under #horseclass = 17). In terms of pose estimation, other available datasets that allow detailed tracking of animal parts are Animal-Pose and Animal Kingdom [100]. In addition to datasets, several models have been proposed for animal pose estimation. Among these, there are Lightning Pose [101], which uses semi-supervised learning and a network architecture with temporal context to make pose predictions more consistent and realistic, and DeepLabCut, an open-source platform

for animal pose estimation [102]. This platform provides semi-automated interfaces for annotating, improving and verifying trajectories. To effectively process this information and apply machine learning models, considerations about cameras and frame rates become essential. Resolution is not typically a limiting issue in machine learning applications. Deep neural networks perform efficiently with input of around  $200 \times 200$  pixels at  $\sim 25$ fps. Multi-camera settings are often useful for capturing opposite perspectives and avoiding blind areas [93]. Convolutional Neural Networks (CNNs) are particularly useful in image processing tasks such as classification and object recognition, mapping different individual inputs to distinct outputs [103]. While reading the input data according to its dimensions, the convolution layer (CONV) uses filters, also referred to as kernels, that carry out a convolutional operation [63]. With the use of CNNs it is possible to recognise patterns in movement that indicate stress or discomfort allowing early intervention and enabling the interpretation of specific behaviours such as lameness in horses [104,105]. One of the benefits of video-based analysis is that they are non-invasive [106], implying they do not cause discomfort to the animal by interfering with its welfare. Furthermore, using a neural network can outperform human performance in cases of mild pain [97].

Researchers have demonstrated how the use of artificial intelligence in equine monitoring can be applied to different purposes [107]. For example [108], presented an approach for animal pose estimation using unsupervised domain adaptation techniques. The suggested method combines synthetic data derived from Computer-Aided Design (CAD) models with an adaptation process that generates pseudo labels, which are then gradually improved using a coarse-to-fine update strategy. This structure allows the model to gradually update the pseudo-labels, improving their accuracy throughout training. The model was trained on a synthetic dataset that included images of horses and tigers, and it was then tested on real-world data from datasets such as TigDog and VisDA 2019. Among the limitations of this approach, the reduced variability of poses in the synthetic data compared to the real one can be highlighted, reducing the model's ability to adapt and learn to the wide range of poses. Moreover, the application of Computer Vision can also be extended to other fields, such as horse racing [109]. Computer Vision systems can monitor and analyse horse activities in real-time during races. One of the main functions of vision in this context is pose estimation, which allows detailed analysis of movements and identifying early detection of signs of injury or fatigue [109]. One of the main challenges could be the many occlusions that occur throughout a race. Horses typically run closely side by side and overlap with each other.

Additionally, accelerometer data can be used in combination with CNNs to automatically classify horse actions [110]. used Axivity AX3 triaxial accelerometers mounted laterally on the tendon boots of the horses' front legs. These sensors have a frequency range from 12.5 to 3200 Hz and a maximum sensitivity of  $\pm 16$  g this data was associated with video recordings as a visual reference with activities manually annotated using ELAN software. The model was trained using the Adam optimiser for 400 epochs. The model was able to distinguish walking activity based on topography with high precision, with an accuracy of  $>93\%$  [110]. The relatively small sample size (six horses) may limit the robustness of the model and although the Axivity AX3 accelerometers are sophisticated, they may have limits in capturing very rapid or complicated motions, particularly under stressful settings. Addressing these critical issues may need more studies and a wider range of data to guarantee that the model is applicable in real-world scenarios.

As already indicated, computer vision techniques can be used to identify emotional states in horses based on their facial expression [111, 112]'s research focusing on developing AI models capable of distinguishing between four emotional states using two different approaches. The first pipeline relies on video data processed with the Grayscale Short-Term stacking (GrayST) method, which captures motion between frames. The second approach, based on EquiFACS, uses manual annotations of facial expressions. Key elements coded include

movements of the lips, eyes, ears and other areas of the face. The results show that the first approach achieved an accuracy of 76 % in classifying the four emotional states, while the EquiFACS model achieved 69 %. Overall, the dataset used included 296 video samples collected from 31 horses, with each animal being filmed in four distinct emotional conditions. Other studies have attempted to develop automated systems capable of assessing pain in horses by analysing their facial expressions [95]. advanced this effort by creating CNN models specific to each area of the horse's face. The algorithm achieved an overall accuracy of 75.88 % when classifying images into three levels of pain and an 88.3 % accuracy for binary classification. The study used Intelbras VHD 12220 B-G4 Multi HD cameras to capture videos from which were manually selected 3000 images that best represented the horse's face expression in varied levels of pain.

**3.2.2.1. Accuracy and reliability.** A number of studies have effectively reported how computer vision technologies may be used to study horse behaviour and how useful these technologies may be for a variety of applications. Video analysis using CNNs reported that pain in horses can be assessed through videos, achieving 88.3 % accuracy in binary classification (pain present vs. absent) [95]. Equine activity monitoring has also been automated with CNNs applied to accelerometer data, achieving up to 99 % classification accuracy for seven behaviours monitored in horses and over 97 % accuracy for unseen subjects [110]. The CARE model was trained and tested on the large-scale Animal Kingdom Dataset, which includes over 50 h of annotated video and enables high-performance action recognition, pose estimation, and video grounding across 850 species [100]. DeepLabCut, a widely used markerless pose estimation tool, was reported with tracking performance comparable to human accuracy with as few as 200 labelled frames [113]. Lightning Pose further advanced this field by incorporating semi-supervised learning, achieving more accurate and reliable pose trajectories via motion continuity, geometry, and smoothing techniques [101]. A smartphone-based markerless motion capture system for equine lameness detection was evaluated against a gold standard multi-camera optical motion capture, reporting a mean difference of 2.2 mm for vertical head and pelvis displacements [105]. Similarly, the non-invasive use of thermal imaging for monitoring calves' vital signs, with Mean Absolute Percentage Errors (MAPE) of 3.08 % for respiration and 3.15 % for heart rate, highlights its potential for PLF [106]. The field of horse management and performance enhancement is increasingly AI-assisted, using intelligent systems to improve the early diagnosis of health and locomotion disorders [107] as well as assist in race prediction, performance evaluation, and provide safety measures during racing [109]. Moreover, the use of multi-scale domain adaptation modules that fuse synthetic and real data were reported to enhance the accuracy of animal pose estimation [108]. There is also the Horse Facial Action Coding System (EquiFACS), which is used in interpreting and describing the horse's facial expressions, and has also facilitated the recognition of frustration among other emotions [111]. Finally, a CNN-based system was developed to classify four emotional states (baseline, positive anticipation, disappointment, and frustration), achieving an overall of 76 %, further supporting the use of AI for real-time affective state detection in equines [112].

**3.2.2.2. Applicability.** The use of computer vision systems to assess equine welfare and behaviour in controlled settings is increasingly widespread while still limited in the field. In fact, the authors report some significant limitations. One of the main ones is the reliance on restricted and often inaccessible databases, combined with the need to use complex software and hardware that require specialised training of personnel [100,102,108,109,113]. In addition, some sensors, such as DeepLabCut and Seek Thermal Compact, were reported as limited in assessing rapid animal movements [106,107,113]. Other instruments, such as CNN, CARE Model, Lightning Pose, EquiFACS, iPhone 12 Pro

Max, and multi-camera marker-based systems, were described as sensitive to environmental factors such as temperature and humidity [95, 100, 102, 110, 111, 113]. Studies also report difficulties with CNN in distinguishing similar emotional states [112]. Table 6 summarises the sensors cited in this subsection.

### 3.3. Technology limitations, data privacy and security

Despite important advances in equine monitoring technology, there

are still significant limitations that need to be addressed to promote the efficient and safe use of these solutions. One of the main issues involves the accuracy and reliability of sensors, particularly in the different climatic conditions typical of equestrian environments. For example, non-wearable technology may be impacted by poor illumination or visual obstruction, while wearable sensors can be impacted by sweating, excessive movement or inaccurate placement. Moreover, the integration and analysis of collected data may represent another challenge. The lack

**Table 6**  
Summary of studies validating computer vision technology.

Technology	Used data	Parameters monitored	Validation context and conditions	Applicability	Limitations	References
Convolutional Neural Network (CNN)	Horse video recordings	Detect and classify pain in horses	Compared with HGS; 88.3 % accuracy for binary pain classification	Applied for real-time monitoring in clinical and research settings	Sensitive to light, device angle, noise, dust and motion; requires specific hardware	[95]
CARe Model	Animal Kingdom Dataset	General animal behaviour understanding	Tested internally with benchmark dataset; strong performance on unseen species	Used for monitoring individuals and groups	Dependent on database variety; high storage needs; expensive, sensitive to environmental factors	[100]
Lightning Pose	Animal videos	Animal pose detection	Evaluated using semi-supervised metrics with multi-view constraints; high pose accuracy reported	Reported as versatile across contexts	Affected by lighting, device angle, reflective surfaces, dust and water	[101]
DeepLabCut	Animal videos	Animal pose estimation, identification and tracking	Compared with human labels and test frames; accuracy comparable to human-level annotation (~ 95 %)	Used for behavioural assessment	Computationally complex, accuracy depends on database variety	[102]
Markerless single camera system (iPhone12 Pro Max) & Multi-camera marker-based system (Qualisys Track Manager)	Smartphone recordings & motion capture data	Lameness detection	Compared with optical motion capture system; mean error under 2.2 mm for head and pelvis	Used for group monitoring in controlled and grazing settings	Sensitive to light, rain and visual disturbances; needs specific stable setup (e.g., tripod)	[105]
DeepLabCut	Animal videos	Pose estimation	Tested using labelled frames and multi-animal benchmarks; accuracy ~ 95 % for various tasks	Applied for analysing complex movements regardless of lighting conditions	Computationally complex; limited for multi-animal interactions and movements; sensitive to poor lighting	[113]
Seek Thermal Compact Pro camera	Thermal images of calves	Non-invasive monitoring of vital signs in calves	Compared with respiration and heart rate sensors; MAPE 3.08 % (respiration), 3.15 % (heart rate)	Reported as applicable for individual and group monitoring in controlled settings	Sensitive to movement, wind, rain and temperature extremes	[106]
AI in horse practice	Medical imaging, videos of horse movement, and facial expression data	Enhancing equine health diagnostics through early detection of problems	Evaluated via correlation with clinical outcome and expert annotations; quantitative metrics not always reported	Used for individual monitoring in controlled settings (clinics, labs)	Sensitive to rapid movement, obstacles, light and temperature changes; requires specific hardware; limited datasets	[107]
Multi-scale domain adaptation module	Synthetic and real-world animal pose data	Pose estimation	Compared with synthetic and real annotated data; superior performance in cross-domain benchmarks	Reported as suitable for individuals and groups in controlled and grazing settings	Require specific hardware, accuracy depends on database; high computational needs (e.g., high-performance GPUs)	[108]
AI in horse racing	Race footage and historical race data	Enhance race predictions, improve betting accuracy, and monitor performance and safety	Compared with betting outcomes and race performance data; statistical improvements in prediction models	Applied for training and competition monitoring	Limited data; computationally complex; sensitive to environment; expensive	[109]
Convolutional Neural Network (CNN)	Accelerometer data from horses	Automatic equine activity detection	Compared with labelled accelerometer data; >99 % accuracy	Applied for welfare and behavioural monitoring	Reduced accuracy on uneven terrain; limited data; expensive; requires high-performance hardware	[110]
Horse Facial Action Coding System (EquiFACS)	Video recordings of horse facial expressions	Recognising frustration in horse facial expressions	Validated against emotion-eliciting scenarios with statistical test; accuracy not quantitatively specified	Reported as suitable for welfare and behavioural monitoring in controlled settings	Sensitive to environment; limited to visible movement	[111]
Convolutional Neural Networks (CNN)	Videos of horses in controlled experimental scenarios	Recognising emotional states from facial expressions	Compared with EquiFACS annotations and controlled emotional states; 76 % multi-class emotion classification accuracy	Reported as applicable in controlled settings; potential for field use	Difficulty in differentiating similar emotions; computationally complex	[112]

of standardisation in data formats and validation processes complicates the integration of data from different devices. This limits the applicability of systems to different contexts and restricts their use for specific circumstances. With regard to data privacy and security, the adoption of these technologies raises important considerations: the information collected during equine monitoring could be subject to unauthorised access, especially when coupled with private owner information.

Based on the current findings, a multidisciplinary approach combining researchers, technology developers and veterinarians will be necessary to overcome these limitations. Optimising the opportunities of monitoring technology while maintaining data security and horse welfare is only possible through constant improvements and return on investment for equine applications. The final aspect to consider is the absence of robust cost-benefit analysis. It is difficult for horse owners to determine whether investing in PLF technologies gives sufficient economic return. Without data on installation costs, the decision to adopt these tools remains limited. Future studies should prioritise confronting these aspects in addition to the continuous improvements of technological advancements to support sustainable decisions.

#### 4. Future perspectives and conclusions

In conclusion, this review has mapped the available monitoring technologies for horses, focusing on wearable and non-wearable devices. Wearable sensors, such as those used to measure HR, HRV, RR, body temperature, accelerometers, GPS devices have been reported as used for collecting physiological data in real time. Meanwhile, non-wearable technologies have been described as supporting equine behavioural monitoring, often without interfering with natural behaviour. Beyond listing technologies, this review summarised reported validation approaches, data accuracy, and applicability. Where available, quantitative information was reported to support comparisons. Although many of these technologies were reported as applicable and valid within specific research or clinical contexts, there are still certain limitations. These include the need for more rigorous validation and the availability of tools that are accessible to a wide range of users. In the future, improvements in equine health and monitoring could be facilitated by the development of more accurate, robust, animal- and user-friendly devices, as well as the incorporation of advanced data analytics, promoting the advancement of research and practical applications in this field.

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All authors agree that:

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That generative AI and AI-assisted technologies have not been utilized in the writing process or if used, disclosed in the manuscript the use of AI and AI-assisted technologies and a statement will appear in the published work.

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#### CRediT authorship contribution statement

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#### References

- [1] Broom DM. A history of Animal welfare science. *Acta Biotheor* 2011;59(2): 121–37. <https://doi.org/10.1007/s10441-011-9123-3>.
- [2] Hill SP, Broom DM. Measuring zoo animal welfare: theory and practice. *Zoo Biol* 2009;28(6):531–44. <https://doi.org/10.1002/zoo.20276>.
- [3] Harst JE, Spruijt B. Tools to measure and improve animal welfare: reward-related behaviour. *Anim Welfare* 2007;16. <https://doi.org/10.1017/S0962728600031742>.
- [4] Whay HR, Main DCJ, Green LE, Webster AJF. Assessment of the welfare of dairy cattle using animal-based measurements: direct observations and investigation of farm records. *Vet Rec* 2003;153(7):197–202. <https://doi.org/10.1136/vr.153.7.197>.
- [5] Webster J. Animal welfare: freedoms, dominions and “A life worth living”. *Animals (Basel)* 2016;6(6):35. <https://doi.org/10.3390/ani6060035>.
- [6] Fraser D. Animal ethics and animal welfare science: bridging the two cultures. *Appl Anim Behav Sci* 1999;65(3):171–89. [https://doi.org/10.1016/S0168-1591\(99\)00090-8](https://doi.org/10.1016/S0168-1591(99)00090-8).
- [7] Mellor DJ. Updating Animal Welfare thinking: moving beyond the “Five Freedoms” towards “A life worth living”. *Animals (Basel)* 2016;6(3):21. <https://doi.org/10.3390/ani6030021>.
- [8] Lamanna M, Buonaiuto G, Colleluori R, Raspa F, Valle E, Cavallini D. Time-activity budget in horses and ponies: a systematic review and meta-analysis on feeding dynamics and management implications. *J Equine Vet Sci* 2025;105684. <https://doi.org/10.1016/j.jevs.2025.105684>.
- [9] Lesimple C. Indicators of Horse welfare: state-of-the-art. *Animals* 2020;10(2). <https://doi.org/10.3390/ani10020294>. Art. no. 2.
- [10] Kang H, Zsoldos RR, Sole-Guitart A, Narayan E, Cawdell-Smith AJ, Gaughan JB. Heat stress in horses: a literature review. *Int J Biometeorol* 2023;67(6):957–73. <https://doi.org/10.1007/s00484-023-02467-7>.
- [11] Siguín M, Blanco T, Rossano F, Casas R. Modular E-collar for animal telemetry: an animal-centered design proposal. *Sensors* 2021;22(1):300. <https://doi.org/10.3390/s22010300>.
- [12] Giannone C, et al. Automated dairy cow identification and feeding behaviour analysis using a computer vision model based on YOLOv8. *Smart Agric Technol* 2025;12:101304. <https://doi.org/10.1016/j.atech.2025.101304>.

- [13] Bovo M, Agrusti M, Benni S, Torreggiani D, Tassinari P. Random forest modelling of milk yield of dairy cows under heat stress conditions. *Animals* 2021;11(5). <https://doi.org/10.3390/ani11051305>.
- [14] Corazzin M, et al. Heat stress and feeding behaviour of dairy cows in late lactation. *Ital J Anim Sci* 2021;20(1):600–10. <https://doi.org/10.1080/1828051X.2021.1903818>.
- [15] Tricco AC, et al. PRISMA extension for scoping reviews (PRISMA-ScR): checklist and explanation. *Ann Intern Med* 2018;169(7):467–73. <https://doi.org/10.7326/M18-0850>.
- [16] Kapteijn CM, et al. Measuring heart rate variability using a heart rate monitor in horses (*Equus caballus*) during groundwork. *Front Vet Sci* 2022;9:939534. <https://doi.org/10.3389/fvets.2022.939534>.
- [17] Galli A, Montree R, Que S, Peri E, Vullings R. An overview of the sensors for heart rate monitoring used in extramural applications. *Sensors* 2022;22(11). <https://doi.org/10.3390/s22114035>. Art. no. 11.
- [18] Miller M, Byfield R, Crosby M, Schiltz P, Johnson PJ, Lin J. A wearable photoplethysmography sensor for non-invasive equine heart rate monitoring. *Smart Agric Technol* 2023;5. <https://doi.org/10.1016/j.atech.2023.100264>.
- [19] Li K, Cardoso C, Moctezuma-Ramirez A, Elgalad A, Perin E. Heart rate variability measurement through a smart wearable device: another breakthrough for personal health monitoring? *Int J Environ Res Public Health* 2023;20(24). <https://doi.org/10.3390/ijerph20247146>. Art. no. 24.
- [20] G. Van Steenkiste, G. van Loon, A. Declodet, G. Crevecoeur, and tammo delhaas, 'Equine electrocardiography revisited: 12-lead recording, vectorcardiography and the power of machine intelligence', 2020.
- [21] Norton T, Piette D, Exadaktylos V, Berckmans D. Automated real-time stress monitoring of police horses using wearable technology. *Appl Anim Behav Sci* 2018;198:67–74. <https://doi.org/10.1016/j.applanim.2017.09.009>.
- [22] Scopa C, et al. Inside the interaction: contact with familiar humans modulates heart rate variability in horses. *Front Vet Sci* 2020;7:582759. <https://doi.org/10.3389/fvets.2020.582759>.
- [23] Mott R, Dowell F, Evans N. Use of the Polar V800 and Actiheart 5 heart rate monitors for the assessment of heart rate variability (HRV) in horses. *Appl Anim Behav Sci* 2021;241:105401. <https://doi.org/10.1016/j.applanim.2021.105401>.
- [24] Woort F, et al. Validation of an equine fitness tracker: ECG quality and arrhythmia detection. *Equine Vet J* 2023;55(2):336–43. <https://doi.org/10.1111/evj.13565>.
- [25] Ter Woort F, Dubois G, Didier M, Van Erck-Westergren E. Validation of an equine fitness tracker: heart rate and heart rate variability. *CEP* 2021;17(2):189–98. <https://doi.org/10.3920/CEP200028>.
- [26] McCrae P, Spong H, Golestani N, Mahnam A, Bashura Y, Pearson W. Validation of an Equine smart textile system for heart rate variability: a preliminary study. *Animals (Basel)* 2023;13(3):512. <https://doi.org/10.3390/ani13030512>.
- [27] Davie A, Beavers R, Hargitaiová K, Denham J. The emerging role of hypoxic training for the equine athlete. *Animals* 2023;13(17):2799. <https://doi.org/10.3390/ani13172799>.
- [28] Matsumoto T, Okumura S, Hirata S. Non-contact respiratory measurement in a horse in standing position using millimeter-wave array radar. *J Vet Med Sci* 2022;84(10):1340–4. <https://doi.org/10.1292/jvms.22-0238>.
- [29] Bizzotto D, et al. A portable fan-based device for evaluating lung function in horses by the forced oscillation technique. *Physiol Meas* 2022;43(2):025001. <https://doi.org/10.1088/1361-6579/ac522e>.
- [30] Andrade FSRM, et al. The optimal PEEP after alveolar recruitment maneuver assessed by electrical impedance tomography in healthy horses. *Front Vet Sci* 2022;9:1024088. <https://doi.org/10.3389/fvets.2022.1024088>.
- [31] Ambrisko TD, Lammer V, Schramel JP, Moens YPS. *In vitro* and *in vivo* evaluation of a new large animal spirometry device using mainstream CO<sub>2</sub> flow sensors. *Equine Vet J* 2014;46(4):507–11. <https://doi.org/10.1111/evj.12140>.
- [32] Kozłowska N, Wierzbicka M, Jasiński T, Domino M. Advances in the diagnosis of equine respiratory diseases: a review of novel imaging and functional techniques. *Animals* 2022;12(3):381. <https://doi.org/10.3390/ani12030381>.
- [33] Asti V, Ablondi M, Molle A, Zanotti A, Vasini M, Sabbioni A. Inertial measurement unit technology for gait detection: a comprehensive evaluation of gait traits in two Italian horse breeds. *Front Vet Sci* 2024;11:1459553. <https://doi.org/10.3389/fvets.2024.1459553>.
- [34] Bovo M, Santolini E, Barbaresi A, Tassinari P, Torreggiani D. Assessment of geometrical and seasonal effects on the natural ventilation of a pig barn using CFD simulations. *Comput Electron Agric* 2022;193. <https://doi.org/10.1016/j.compag.2021.106652>.
- [35] Giannone C, Bovo M, Ceccarelli M, Torreggiani D, Tassinari P. Review of the heat stress-induced responses in dairy cattle. *Animals* 2023;13(22):3451. <https://doi.org/10.3390/ani13223451>.
- [36] Abeni F, Galli A. Monitoring cow activity and rumination time for an early detection of heat stress in dairy cow. *Int J Biometeorol* 2017;61(3):417–25. <https://doi.org/10.1007/s00484-016-1222-z>.
- [37] Verdegaal E-LJMM, Howarth GS, Mcwhorter TJ, Delesalle CJG, Mota-Rojas D. Thermoregulation during field exercise in horses using skin temperature monitoring. *Animals* 2024;14(1):136. <https://doi.org/10.3390/ani14010136>.
- [38] Brownlow MA, Brotherhood JR. An investigation into environmental variables influencing post-race exertional heat illness in thoroughbred racehorses in temperate eastern Australia. *Aust Vet J* 2021;99(11):473–81. <https://doi.org/10.1111/avj.13108>.
- [39] Han CS, et al. Invited review: sensor technologies for real-time monitoring of the rumen environment. *J Dairy Sci* 2022;105(8):6379–404. <https://doi.org/10.3168/jds.2021-20576>.
- [40] Domino M, et al. The effect of rider:horse bodyweight ratio on the superficial body temperature of horse's thoracolumbar region evaluated by advanced thermal image processing. *Animals* 2022;12(2):195. <https://doi.org/10.3390/ani12020195>.
- [41] Soroko M, Howell K, Dudek K, Wilk I, Zastrzeżyńska M, Janczarek I. A pilot study into the utility of dynamic infrared thermography for measuring body surface temperature changes during treadmill exercise in horses. *J Equine Vet Sci* 2018;62:44–6. <https://doi.org/10.1016/j.jevs.2017.12.010>.
- [42] Soroko M, Howell K. Infrared thermography: current applications in Equine medicine. *J Equine Vet Sci* 2018;60:90–6. <https://doi.org/10.1016/j.jevs.2016.11.002>. e2.
- [43] Johnson SR, Rao S, Hussey SB, Morley PS, Traub-Dargatz JL. Thermographic eye temperature as an index to body temperature in ponies. *J Equine Vet Sci* 2011;31(2):63–6. <https://doi.org/10.1016/j.jevs.2010.12.004>.
- [44] Kim S-M, Cho G-J. Validation of eye temperature assessed using infrared thermography as an indicator of welfare in horses. *Appl Sci* 2021;11(16). <https://doi.org/10.3390/app11167186>. Art. no. 16.
- [45] Masko M, Krajewska A, Zdrojkowski L, Domino M, Gajewski Z. An application of temperature mapping of horse's back for leisure horse-rider-matching. *Anim Sci J* 2019;90(10):1396–406. <https://doi.org/10.1111/asj.13282>.
- [46] Dai F, Cogi NH, Heinzl EUL, Dalla Costa E, Canali E, Minero M. Validation of a fear test in sport horses using infrared thermography. *J Veter Behav* 2015;10(2):128–36. <https://doi.org/10.1016/j.jveb.2014.12.001>.
- [47] Stewart M, Webster JR, Verkerk GA, Schaefer AL, Colyn JJ, Stafford KJ. Non-invasive measurement of stress in dairy cows using infrared thermography. *Physiol Behav* 2007;92(3):520–5. <https://doi.org/10.1016/j.physbeh.2007.04.034>.
- [48] Riaz U, Idris M, Ahmed M, Ali F, Farooq U, Yang L. The potential of infrared thermography for early pregnancy diagnosis in Nili-Ravi buffaloes. *Animals* 2024;14(13):1966. <https://doi.org/10.3390/ani14131966>.
- [49] Witkowska-Pilasiewicz O, Maško M, Domino M, Winnicka A. Infrared thermography correlates with lactate concentration in blood during race training in horses. *Animals* 2020;10(11). <https://doi.org/10.3390/ani10112072>. Art. no. 11.
- [50] Camuffo D. Measuring temperature. *Microclimate for cultural heritage*. Elsevier; 2019. p. 383–429. <https://doi.org/10.1016/B978-0-444-64106-9.00017-1>.
- [51] Geor RJ, McCutcheon LJ, Ecker GL, Lindinger MI. Heat storage in horses during submaximal exercise before and after humid heat acclimation. *J Appl Physiol* 2000;89(6):2283–93. <https://doi.org/10.1152/jappl.2000.89.6.2283>.
- [52] Reesink HL, et al. Measurement of digital lamellar and venous temperatures as a means of comparing three methods of topically applied cold treatment for digits of horses. *ajvr* 2012;73(6):860–6. <https://doi.org/10.2460/ajvr.73.6.860>.
- [53] Burke MJ, Tomlinson JE, Blikslager AT, Johnson AL, Dallap-Schaer BL. 'Evaluation of digital cryotherapy using a commercially available sleeve style ice boot in healthy horses and horses receiving i.v. endotoxin'. *Equine Vet J* 2018;50(6):848–53. <https://doi.org/10.1111/evj.12842>.
- [54] E.-L.J.M.M. Verdegaal et al., 'Evaluation of a telemetric gastrointestinal pill for continuous monitoring of gastrointestinal temperature in horses at rest and during exercise', 2017, [doi: 10.2460/ajvr.78.7.778](https://doi.org/10.2460/ajvr.78.7.778).
- [55] Verdegaal E-LJMM, et al. Continuous monitoring of the thermoregulatory response in endurance horses and trotter horses during field exercise: baselining for future hot weather studies. *Front Physiol* 2021;12:708737. <https://doi.org/10.3389/fphys.2021.708737>.
- [56] Kang H, Zsoldos RR, Skinner JE, Gaughan JB, Mellor VA, Sole-Guitart A. The use of percutaneous thermal sensing microchips to measure body temperature in horses during and after exercise using three different cool-down methods. *Animals (Basel)* 2022;12(10):1267. <https://doi.org/10.3390/ani12101267>.
- [57] Auclair-Ronzaud J, et al. No-contact microchip monitoring of body temperature in yearling horses. *J Equine Vet Sci* 2020;86:102892. <https://doi.org/10.1016/j.jevs.2019.102892>.
- [58] T.R. Robinson, S.B. Hussey, A.E. Hill, C.C. Heckendorf, J.B. Stricklin, and J.L. Traub-Dargatz, 'Comparison of temperature readings from a percutaneous thermal sensing microchip with temperature readings from a digital rectal thermometer in equids', 2008, [doi: 10.2460/javma.233.4.613](https://doi.org/10.2460/javma.233.4.613).
- [59] Maisonnier IN, Sutton MA, Harris P, Menzies-Gow N, Weller R, Pfau T. Accelerometer activity tracking in horses and the effect of pasture management on time budget. *Equine Vet J* 2019;51(6):840–5. <https://doi.org/10.1111/evj.13130>.
- [60] Costa EDalla, et al. Initial outcomes of a harmonized approach to collect welfare data in sport and leisure horses. *Animal* 2017;11(2):254–60. <https://doi.org/10.1017/S1751731116001452>.
- [61] Briggs EV, Mazzà C. Automatic methods of hoof-on and -off detection in horses using wearable inertial sensors during walk and trot on asphalt, sand and grass. *PLoS One* 2021;16(7):e0254813. <https://doi.org/10.1371/journal.pone.0254813>.
- [62] Pickles KJ, Marlin DJ, Williams JM, Roberts VLH. Use of a poll-mounted accelerometer for quantification and characterisation of equine trigeminal-mediated headshaking. *Equine Vet J* 2024. <https://doi.org/10.1111/evj.14132>. vol. n/a, no. n/a.
- [63] Eerdeken A, et al. A framework for energy-efficient equine activity recognition with leg accelerometers. *Comput Electron Agric* 2021;183:106020. <https://doi.org/10.1016/j.compag.2021.106020>.
- [64] Rana M, Mittal V. Horse gait analysis using wearable inertial sensors and machine learning. *Proc Inst Mech Eng, Part P: J Sports Eng Technol* 2023. <https://doi.org/10.1177/17543371231196814>.

- [65] Burla JB, Ostertag A, Westerath HSchulze, Hillmann E. Gait determination and activity measurement in horses using an accelerometer. *Comput Electron Agric* 2014;102:127–33. <https://doi.org/10.1016/j.compag.2014.01.001>.
- [66] Steinke SL, Montgomery JB, Barden JM. Accelerometry-based step count validation for horse movement analysis during stall confinement. *Front Vet Sci* 2021;8. <https://doi.org/10.3389/fvets.2021.681213>.
- [67] Crecan CM, Peştean CP. Inertial sensor technologies-their role in equine gait analysis, a review. *Sensors (Basel)* 2023;23(14). <https://doi.org/10.3390/s23146301>.
- [68] Morrison R, et al. Validity and practical utility of accelerometry for the measurement of in-hand physical activity in horses. *BMC Vet Res* 2015;11(1):233. <https://doi.org/10.1186/s12917-015-0550-2>.
- [69] Eerdeken A, et al. Horse jumping and dressage training activity detection using accelerometer data. *Animals* 2021;11(10):2904. <https://doi.org/10.3390/ani11102904>.
- [70] Morrice-West AV, Hitchens PL, Walmsley EA, Stevenson MA, Wong ASM, Whitton RC. Variation in GPS and accelerometer recorded velocity and stride parameters of galloping thoroughbred horses. *Equine Vet J* 2021;53(5):1063–74. <https://doi.org/10.1111/evj.13370>.
- [71] Crecan CM, Morar IA, Lupsan AF, Repciuc CC, Rus MA, Peştean CP. Development of a novel approach for detection of equine lameness based on inertial sensors: a preliminary study. *Sensors* 2022;22(18). <https://doi.org/10.3390/s22187082>.
- [72] Yigit T, Han F, Rankins E, Yi J, McKeever KH, Malinowski K. Wearable inertial sensor-based limb lameness detection and pose estimation for horses. *IEEE Trans Autom Sci Eng* 2022;19(3):1365–79. <https://doi.org/10.1109/TASE.2022.3157793>.
- [73] Eerdeken A, et al. Automatic early detection of induced colic in horses using accelerometer devices. *Equine Vet J* 2024. <https://doi.org/10.1111/evj.14069>.
- [74] Kallerud AS, Marques-Smith P, Bendiksen HK, Fjordbakk CT. Objective movement asymmetry in horses is comparable between markerless technology and sensor-based systems. *Equine Vet J* 2024. <https://doi.org/10.1111/evj.14089>.
- [75] Zetterberg E, et al. Prevalence of vertical movement asymmetries at trot in standardbred and Swedish Warmblood foals. *PLoS One* 2023;18(4):e0284105. <https://doi.org/10.1371/journal.pone.0284105>.
- [76] Kelemen Z, et al. Equine activity time budgets: the effect of housing and management conditions on geriatric horses and horses with chronic orthopaedic disease. *Animals* 2021;11(7). <https://doi.org/10.3390/ani11071867>. Art. no. 7.
- [77] Williams M, Hatto S. Evaluation of accelerometer fitting position, sampling intervals and data editing techniques for measuring equine lying postures when stabled. *Appl Anim Behav Sci* 2023;266:106036. <https://doi.org/10.1016/j.applanim.2023.106036>.
- [78] Sato F, Tanabe T, Murase H, Tominari M, Kawai M. Application of a wearable GPS unit for examining interindividual distances in a herd of thoroughbred dams and their foals. *J Equine Sci* 2017;28(1):13–7. <https://doi.org/10.1294/jes.28.13>.
- [79] Best R, Standing R. Feasibility of a global positioning system to assess the spatiotemporal characteristics of polo performance. *J Equine Vet Sci* 2019;79:59–62. <https://doi.org/10.1016/j.jvevs.2019.05.018>.
- [80] Farmer J, et al. Environmental impacts and daily voluntary movement of horses housed in pasture tracks as compared to conventional pasture housing. *Rochester, NY* 2024:4704692. <https://doi.org/10.2139/ssrn.4704692>.
- [81] Hampson BA, Morton JM, Mills PC, Trotter MG, Lamb DW, Pollitt CC. Monitoring distances travelled by horses using GPS tracking collars. *Aust. Vet. J.* 2010;88(5):176–81. <https://doi.org/10.1111/j.1751-0813.2010.00564.x>.
- [82] Miller M, Byfield R, Crosby M, Lin J. Networked wearable sensors for monitoring health and activities of an equine herd: an IoT approach to improve horse welfare. *IEEE Sens J* 2024;24(18):29211–8. <https://doi.org/10.1109/JSEN.2024.3436665>.
- [83] Darbandi H, et al. Using different combinations of body-mounted IMU sensors to estimate speed of horses—A machine learning approach. *Sensors* 2021;21(3). <https://doi.org/10.3390/s21030798>. Art. no. 3.
- [84] Wong ASM, Morrice-West AV, Whitton RC, Hitchens PL. Changes in thoroughbred speed and stride characteristics over successive race starts and their association with musculoskeletal injury. *Equine Vet J* 2023;55(2):194–204. <https://doi.org/10.1111/evj.13581>.
- [85] Pfau T, Bruce O, Edwards WBrent, Leguillette R. Stride frequency derived from GPS speed fluctuations in galloping horses. *J Biomech* 2022;145:111364. <https://doi.org/10.1016/j.jbiomech.2022.111364>.
- [86] Guyard KC, Montavon S, Bertolaccini J, Deriaz M. Validation of Alogo Move Pro: a GPS-based inertial measurement unit for the objective examination of gait and jumping in horses. *Sensors* 2023;23(9):4196. <https://doi.org/10.3390/s23094196>.
- [87] Maurício LS, Leme DP, Hötzel MJ. How to understand them? A review of emotional indicators in horses. *J Equine Vet Sci* 2023;126:104249. <https://doi.org/10.1016/j.jvevs.2023.104249>.
- [88] Riva MG, Dai F, Huhtinen M, Minero M, Barbieri S, Costa EDalla. The impact of noise anxiety on behavior and welfare of horses from UK and US owner's perspective. *Animals* 2022;12(10):1319. <https://doi.org/10.3390/ani12101319>.
- [89] Janicka W, Wilk I, Próchniak T, Janczarek I. Can sound alone act as a virtual barrier for horses? A preliminary study. *Animals* 2022;12(22):3151. <https://doi.org/10.3390/ani12223151>.
- [90] Nunes L, Ampatzidis Y, Costa L, Wallau M. Horse foraging behavior detection using sound recognition techniques and artificial intelligence. *Comput Electron Agric* 2021;183:106080. <https://doi.org/10.1016/j.compag.2021.106080>.
- [91] Barakzai SZ, Wells J, Parkin TDH, Cramp P. Overground endoscopic findings and respiratory sound analysis in horses with recurrent laryngeal neuropathy after unilateral laser ventriculocordectomy. *Equine Vet J* 2019;51(2):185–91. <https://doi.org/10.1111/evj.12993>.
- [92] Seifert O, Groß V, Weissflog A, Kramer M, Sohrai K. A new method of visualizing lung ventilation by means of breathing sounds. *Pneumologie* 2016;70(07):s-0036-1584382. <https://doi.org/10.1055/s-0036-1584382>.
- [93] Andersen PH, et al. Towards machine recognition of facial expressions of pain in horses. *Animals* 2021;11(6):1643. <https://doi.org/10.3390/ani11061643>.
- [94] Broomé S, et al. Going deeper than tracking: a survey of computer-vision based recognition of animal pain and emotions. *Int J Comput Vis* 2022;131. <https://doi.org/10.1007/s11263-022-01716-3>.
- [95] Lencioni GC, De Sousa RV, De Souza Sardinha EJ, Corrêa RR, Zanella AJ. Pain assessment in horses using automatic facial expression recognition through deep learning-based modeling. *PLoS One* 2021;16(10):e0258672. <https://doi.org/10.1371/journal.pone.0258672>.
- [96] Kim SM, Cho GJ. Analysis of various facial expressions of horses as a welfare indicator using deep learning. *Vet Sci* 2023;10(4):283. <https://doi.org/10.3390/vetsci10040283>.
- [97] Broomé S, Ask K, Rashid-Engström M, Haubro Andersen P, Kjellström H. Sharing pain: using pain domain transfer for video recognition of low grade orthopedic pain in horses. *PLoS One* 2022;17(3):e0263854. <https://doi.org/10.1371/journal.pone.0263854>.
- [98] Fernandes AFA, Dórea JRR, de GJ, Rosa M. Image analysis and computer vision applications in Animal sciences: an overview. *Front Vet Sci* 2020;7. <https://doi.org/10.3389/fvets.2020.551269>.
- [99] Lin T-Y, et al. Microsoft COCO: common objects in context. In: Fleet D, Pajdla T, Schiele B, Tuytelaars T, editors. *Computer vision – ECCV 2014*. Computer vision – ECCV 2014, 8693. Cham: Springer International Publishing; 2014. p. 740–55. [https://doi.org/10.1007/978-3-319-10602-1\\_48](https://doi.org/10.1007/978-3-319-10602-1_48). Lecture Notes in Computer Science8693.
- [100] Ng XL, Ong KE, Zheng Q, Ni Y, Yeo SY, Liu J. Animal Kingdom: a large and diverse dataset for Animal behavior understanding. In: *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. New Orleans, LA, USA: IEEE; 2022. p. 19001–12. <https://doi.org/10.1109/CVPR52688.2022.01844>.
- [101] D. Biderman et al., 'Lightning Pose: improved animal pose estimation via semi-supervised learning, bayesian ensembling, and cloud-native open-source tools', 2024.
- [102] Lauer J, et al. Multi-animal pose estimation, identification and tracking with DeepLabCut. *Nat Methods* 2022;19(4):496–504. <https://doi.org/10.1038/s41592-022-01443-0>.
- [103] Chiavaccini L, Gupta A, Chiavaccini G. From facial expressions to algorithms: a narrative review of animal pain recognition technologies. *Front Vet Sci* 2024;11. <https://doi.org/10.3389/fvets.2024.1436795>.
- [104] Feuser A-K, Gesell-May S, Müller T, May A. Artificial intelligence for lameness detection in horses—A preliminary study. *Animals (Basel)* 2022;12(20):2804. <https://doi.org/10.3390/ani12202804>.
- [105] Lawin FJ, et al. Is markerless more or less? Comparing a smartphone computer vision method for equine lameness assessment to multi-camera motion capture. *Animals* 2023;13(3):390. <https://doi.org/10.3390/ANI13030390>. –390.
- [106] E. Sadeghi, Z. Guo, A. Chiumento, and P. Havinga, *Non-invasive monitoring of vital signs in calves using thermal imaging technology*. 2024.
- [107] Graham C. The potential impact of artificial intelligence in equine practice. *UK Vet Equine*. Accessed: Y 18, <https://www.ukvetequine.com/content/clinical/the-potential-impact-of-artificial-intelligence-in-equine-practice/>; 2024.
- [108] Li C, Lee GH. From synthetic to real: unsupervised domain adaptation for animal pose estimation. 27, <http://arxiv.org/abs/2103.14843>; 2021.
- [109] P. Colle, *What AI can do for horse-racing?* 2022. doi: 10.48550/arXiv.2207.04981.
- [110] Eerdeken A, Deruyck M, Fontaine J, Martens L, Poorter ED, Joseph W. Automatic equine activity detection by convolutional neural networks using accelerometer data. *Comput Electron Agric* 2020;168:105139. <https://doi.org/10.1016/j.compag.2019.105139>.
- [111] Ricci-Bonot C, Mills DS. Recognising the facial expression of frustration in the horse during feeding period. *Appl Anim Behav Sci* 2023;265:105966. <https://doi.org/10.1016/j.applanim.2023.105966>.
- [112] Feigelstein M, et al. Automated recognition of emotional states of horses from facial expressions. *PLoS One* 2024;19(7). <https://doi.org/10.1371/journal.pone.0302893>.
- [113] Mathis A, et al. DeepLabCut: markerless pose estimation of user-defined body parts with deep learning. *Nat Neurosci* 2018;21(9):1281–9. <https://doi.org/10.1038/s41593-018-0209-y>.