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Review Article

Smart Cages, Better Welfare: Supporting the 3Rs in Animal Research With Home-cage Monitoring and System Selection

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Abstract: High welfare standards for animals used in research is as much an ethical issue as it is a cornerstone of high-quality science. Researchers can improve both animal welfare and data reliability by implementing strategies that reduce stress in experimental animals. One modern and effective approach is to monitor animals within their familiar home-cage environment. Home-cage monitoring (HCM) systems integrate multiple approaches to automatically, continuously, and non-invasively monitor the physiology and behaviour of laboratory animals within their home environments. HCM favours the animals' natural rhythms and behaviours while reducing stress from various sources and the need for human intervention. In this article, we explore how HCM contributes to the 3Rs framework introduced by Russell and Burch and focus particularly on how to select the most appropriate HCM system for specific research needs. We discuss available resources and practical limitations for system choice, and provide a brief outlook on the evolving role of artificial intelligence to analyse HCM data. We also discuss the opportunities and barriers to HCM adoption, particularly in relation to countries with developing research structure and limited funding in Europe. Our central message is clear: use of HCM technologies supports 3Rs and promotes both better science and better animal welfare.

Introduction

Animal research remains crucial for progress in the life sciences, for understanding human and animal biology, and for advancing applied animal studies (1). Traditionally, animal research has depended on direct observations and handling to collect data, which can introduce subjective bias that may compromise data integrity (2). Moreover, this approach is not only time-consuming and labour-intensive, but it can also introduce stressors that may disrupt the animals' natural behaviour and confound experimental results. Modern technology, advanced sensors, and computational methods now make it possible to follow animals' behaviour continuously and with minimal human interference. In companion animals, these tools improve our understanding of affective states, supporting both welfare and the human–animal bond (3). In farm settings, similar approaches can be applied to monitor the wellbeing of production animals. For example, welfare assessments in poultry (4) can be supported by automated systems for non-invasive and 24/7 real-time monitoring, while accelerometers have been used to track physical activity and detect welfare-related changes in pigs and cattle (5).

In laboratory animal science, monitoring animals ranges from purely direct methods, such as clinical scoring and ethograms, to semi-automated techniques like radio-frequency identification (RFID) tracking, implanted telemetry for temperature or electrocardiography (ECG), and video/computer vision systems (6, 7). Modern home-cage monitoring (HCM) systems integrate several of these approaches to automatically, continuously, and non-invasively collect data on the physiology and behaviour of laboratory animals in their home environment (8-12). A recent systematic review of more than 500 scientific papers maps this evolution, showing a gradual shift from brief, observational tests toward 24/7 automated techniques since the 2000s, while highlighting that direct assessments still have roles in certain endpoints and validations (13). Compared with tests outside the home cage, HCM can reduce handling/separation from social groups (which can alter behaviour and welfare) and records full circadian patterns, improving both experimental validity and reproducibility (9, 14). At first glance, an HCM cage appears similar to a traditional cage but incorporates various technologies. To turn a traditional cage into an HCM, a variety of sensors can be installed, such as a video camera, RFID, *lickometers*, gas sampling ports for metabolic measurements, etc. Figure 1 presents a visual description and design of how an HCM differs from a traditional laboratory cage.

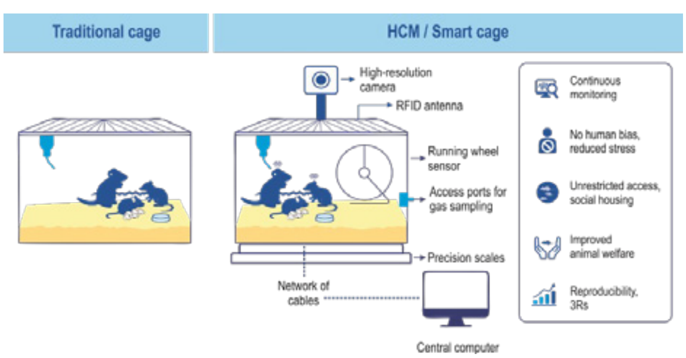

Figure 1: Benefits of HCM systems for laboratory animals

By generating continuous datasets across days or weeks, HCM provides a rich, longitudinal dataset that reflects the animal's natural and spontaneous state. In oncology, neurosciences, and ageing studies, HCM-measured activity and rest metrics have moreover been validated as sensitive biomarkers, further supporting its efficiency and translational relevance (15, 16).

The quantity of data produced through animal experiments is advancing our understanding of animal behaviour, health, and welfare and can help support the 3Rs (Replacement, Reduction, and Refinement) in animal research. These 3Rs principles, introduced by Russell and Burch in 1959 (17), form the ethical and legal basis for animal research worldwide. Replacement promotes the use of alternatives, such as *in vitro* models, computer simulations, ethically sourced human tissue, organoids, or organ-on-chip systems. Reduction aims to use fewer animals without compromising scientific validity, obtaining more data without using more animals, while Refinement aims to minimise distress and improve animal welfare during experimental procedures (17). Thus, HCM systems offer a modern automated approach for 24/7 data collection and real-time monitoring of animals in their home environment, which has the potential to improve experimental reproducibility, while strengthening adherence to the 3Rs.

Advancing the 3Rs principles through HCM

HCM systems represent a significant advancement for 3Rs principles, in biomedical research. A central challenge in behavioural neuroscience is high inter-individual variability, reducing the signal (said variability) to noise (any treatment difference one wishes to detect) ratio, thus demanding larger sample sizes to detect any existing treatment effects. Much of this variability arises from handling- and environment-induced stress, such as repeated transport, lighting changes, noise, cage cleaning, and exposure to novel arenas, which can unpredictably affect physiology and behaviour (18). HCM allows capturing an animal's dramatype in a more familiar and undisturbed fashion, and thus closer to the natural phenotype being studied. In contrast, conventional snapshot testing (9) captures only how animals react in a very specific setting (the testing apparatus) and during a short period, i.e. a very narrow and unrepresentative dramatype (e.g. animals being tested for activity during their inactive period, or under stress from social isolation and other stressors). By enabling within-subject longitudinal comparisons (19-21), in an undisturbed setting, HCM reduces between-animal residual variance, and likely lead to decreasing the number of animals required per experiment (20, 22), as seen in other contexts, such as studies on lung cancer progression in mice using *in vivo* micro-CT imaging, where longitudinal imaging (on the same animals at 2, 3, and 4 months) enables detection of tumour growth metrics with smaller sample sizes, as the information from repeated measures increases the sensitivity of the test (23). Even with HCM, cage effects remain a non-negligible source of structured variance. Cage-mates share microenvironments (ventilation, bedding, and enrichment), social interaction, and possibly shared handling history, making their responses statistically non-independent. Neglecting to control for cage identity risks pseudoreplication, and could bias the outcomes of an experiment (24). The correct approach is to employ randomized block designs with cage as block, and also have cage as a random effect within statistical modelling (25). Moreover, the high-resolution datasets generated by HCM are, besides the initial experiment, valuable because they can be reused for retrospective studies, multiple analyses, or development and validation of *in silico* models (7, 19), which may lead to the potential reduction in animal use, and even its Replacement.

Recently, Blenkuš et al. (2022) (26) demonstrated that even short handling periods in mice (with either tail-picking or tunnel-handling techniques) elicit significant stress-induced hyperthermia, consistent across strains and sexes, and this effect persists even after days of gentle daily handling, suggesting mice do not get habituated to it. Minimizing handling stress through HCM is therefore a significant Refinement for these species. Moreover, HCM is compatible with housing animals in well-resourced – the so-called "enriched" – home cages, with social housing and species-suitable features such as bedding, nesting material, shelter and tunnels, thus supporting naturalistic behaviour (7) (Fig. 1). Automated data collection also minimises experimenter bias and stress, while maximising both welfare and scientific validity (8, 27, 28). HCM setups enable early detection of behavioural or health changes that are critical after invasive procedures like intracranial surgery, without the need for direct handling (16, 20, 29, 30). Moreover, continuous monitoring of behavioural (e.g. activity, speed, gait) and physiological parameters (e.g. heart rate, temperature) can signal "points of no-return" (e.g. non-transient hypothermia (31)) that can be used as humane endpoints, allowing early intervention to treat animals or remove them from the experiment, preventing avoidable suffering. These humane endpoints and continuous welfare monitoring are not only ethical obligations but also enhance scientific rigor by reducing variability and improving data quality (32).

Overall, HCM technologies support all the 3Rs by offering large datasets that can train *in silico* models or used as reliable historical data (Replacement); minimise variability, allow continuous intra-individual comparisons, and obtain more data without using more animals (Reduction); and by reducing handling stress, allowing naturalistic environments and social interactions, and providing a tool for continuous monitoring of behavioural and physiological parameters that can inform the health and welfare status of animals.

HCM vs. conventional systems in light of the 3Rs

While traditional methods have been foundational in animal studies, they introduce multiple stressors, such as environmental changes, handling, restraint, unfamiliar conditions (holding cages, mazes), and social disruption (33-35), that compromise animal welfare and research quality. Researchers can mitigate these stressors and improve both animal well-being and data reliability by using strategies like desensitisation (positive handling), environmental enrichment, social housing, and habituation to procedures through gradual exposure (36-41). However, if these strategies are inconsistently applied or documented, it can limit experiment reproducibility (42-44). Moreover, the concept of animal welfare has evolved beyond simply preventing disease or neglect. Modern science guided by the concept of the Five Freedoms and, more recently, the Five Domains (nutrition, environment, health, behaviour, and mental state), now aims to promote a positive affective state (45). Measuring this complex state requires a multifaceted approach from coarse endpoint measures to continuous, holistic, and non-invasive monitoring. To achieve this, housing systems have shifted from standardised, minimalistic environments to complex, species-specific habitats that meet the animal's physiological and behavioural needs (13).

The adoption of HCM systems offers an alternative path toward a paradigm of continuous welfare assessment compared to conventional systems. HCM provides a more accurate representation of natural animal behaviour, contributing to the advancement of more humane and reproducible research practices. Table 1 summarises how HCM systems enhance traditional animal testing methods by providing continuous, non-invasive, and context-rich data.

Choosing the right HCM system

HCM systems have demonstrated their capacity to support the 3Rs principles, however, selecting the right HCM system involves consideration of several factors and is a process beyond just choosing the cage setup. In practice, it requires aligning the system's capabilities with specific research needs, evaluating financial feasibility through cost-effectiveness analysis, and ensuring long-term utility.

Factors influencing the selection of an HCM system

The specific behavioural parameters to be investigated are the primary determinants of choosing an HCM system, as different systems vary in their ability to monitor particular behaviours (13, 63). For example, the IntelliCage system allows the study of social interactions and operant conditioning in group-housed animals, whereas the PhenoTyper system excels in precise locomotor activity tracking (6). Some systems, like RodentWatch, leverage deep learning algorithms to accurately differentiate basic rodent behaviours using only video input, thus requiring simpler setups without specialised sensors (64). These AI-powered systems streamline monitoring by relying solely on video data.

Compatibility with the specific animal strain is also important, considering factors such as cage size, sensor placement, and behavioural or physiological characteristics unique to that strain (65). When studying social behaviour, group housing is essential. Therefore, only systems designed to monitor multiple animals simultaneously can be used. Such systems must support group settings and capture interactions and social hierarchies (6). While group housing poses technical challenges, especially in systems

Table 1: Comparison of conventional methods and HCM with 3Rs benefits

Conventional method	HCM alternative	Potential advantages offered by HCM integrated with home cage of animals	Enhancing the R
Open field test (OFT) Used to assess anxiety-like behaviour and general locomotion by placing an animal in a novel, brightly lit arena for a short time	**Circadian locomotion and thigmotaxis monitoring** Tracks daily activity patterns and wall-hugging behaviour continuously in the familiar home cage	– Behaviour can be measured in a familiar environment, avoiding the artificial stress caused by a new arena (46) – Can provide insights into daily rhythms, nocturnal and circadian behaviours, and habituation instead of relying on a single snapshot (14, 47)	Refinement
Observational direct social interaction test A short session in which a novel animal is introduced into a test arena and interactions are scored	**Automated social tracking** Uses RFID and video recording to track interactions between group-housed animals continuously	– Captures genuine social dynamics in group-housed conditions (48) – Provides continuous, unbiased data on social behaviour – Automated analysis avoiding human scoring errors	Refinement Reduction
Forced swim test (FST) / Tail suspension test (TST) Measures depressive-like behaviour by recording immobility when animals face an inescapable stressor (49-51)	**Spontaneous behaviour monitoring (e.g., grooming, burrowing, nesting)** Assesses motivation and self-care behaviours continuously in the home cage	– More ethical approach and avoids exposing animals to severe acute stress while focusing on natural behaviours (52) – Continuous monitoring of grooming and nesting behaviour provides more reliable measurement of depression-like behaviour as well as reduced welfare (52-54)	Refinement Replacement
Novel object recognition (NOR) test in an open field arena Measures the time spent sniffing the familiar and non-familiar objects outside of the home cage **Conventional T-maze test** Measures the time spent in newly unblocked arm in a T-maze arena	**Automated tracking of sniffing behaviour** Uses RFID and video recording to track interactions of rodents with familiar and unfamiliar objects Uses infrared camera for continuous monitoring of animal activity	– simple test performance, – no expensive supplies or equipment, – NOR conducted in the home cage - reducing stress and eliminating odour confounds (55) – T-maze test within the home cage ("smart-Kage")- without any need of water or food restriction (56)	Refinement Reduction
Direct body weight measurement Animals are weighed manually on a daily or weekly basis, requiring handling and restraint	**Automated platform scales** Animals are weighed passively each time they cross a sensitive scale in their cage	– Eliminates handling, ensuring more reliable weight data unaffected by stress responses (57) – Can detect subtle day-to-day changes missed by weekly measurements	Refinement Reduction
Metabolic caging Animals are placed in specialized barren calorimetry cages for 24–48 hours to measure energy expenditure	**Integrated calorimetry in enriched home cage** Monitors oxygen consumption, CO_2 output, and energy expenditure over long periods in the regular home cage	– Animals remain in their (enriched), familiar environment, giving more accurate metabolic readings less confounded by stress (58) – Enables study of circadian rhythms and metabolic adaptation across weeks	Refinement Reduction
Blood sampling (tail nick or saphenous vein) Measures corticosterone (CORT) levels as a stress marker, but requires restraint and handling	**Voluntary CORT consumption monitoring** Rather provides corticosterone solution in a water bottle, with intake tracked by lickometers	– Completely non-invasive and avoids the stress of capture and blood collection, which itself elevates CORT (59, 60) – Allows continuous monitoring of rhythmicity of adrenal (hormone) activity	Refinement
Behavioural, physiological, and social assays	**Big-data integration and virtual modelling ("virtual mouse")** Computational simulations built from large HCM datasets Abstracting and integrating the outputs of multiple conventional experiments into a predictive model	– Hypothesis testing and drug discovery *in silico* – Aggregation of behavioural, metabolic, and endocrine data into predictive models. For example, 3D synthetic virtual mouse for behavioural training data (61) and group behavioural modelling across cages (62)	Replacement

without individual tagging, it significantly benefits animal welfare.

Data integration and analysis capabilities are crucial factors considering your existing infrastructure and data management policies. It is important to evaluate the system's interface, data export options, and compatibility with statistical software, particularly in the era of big data (19). Ideally, the system should support standard data export formats (e.g., CSV, JSON) and provide access to an application programming interface, enabling seamless integration with tools such as R, Python, or MATLAB for advanced offline analyses.

Cost vs. long-term benefits

PhenoTyper, IntelliCage, and Actual-HCA are premium systems that involve significant initial funds and ongoing operational costs; however, they also offer advanced features that can validate these expenses. On the other side, less expensive home-made systems, such as Raspberry Pi-based systems (66), can support basic observational tasks, making them suitable for studies in resource-limited settings. Financial concerns are, in most cases, a main barrier to HCM adoption, as most systems require complex infrastructure, specialised cages, and additional space for sensors and data processing units.

Mingrone et al. (2020) compared four widely used systems (Chora Feeder, IntelliCage, PhenoTyper, and Actual-HCA) highlighting trade-offs between affordability, spatial requirements, and the scope of behavioural domains addressed (6). For example, the IntelliCage has high initial costs, which may be justified by the possibility of testing several different domains of behaviour in group-housed animals, with a high standardisation of conditions that enables reproducibility of research. The PhenoTyper provides detailed micromovement and behaviour tracking but requires single housing and substantial space, making it more suitable for short-term experimental sessions than long-term housing. The Actual-HCA system enables group-housed monitoring but entails high per-cage costs and specific ventilated-cage requirements, while Chora Feeder is more affordable yet requires individual housing and frequent maintenance.

Ultimately, system choice depends on research goals, budget, and available expertise. Beyond initial costs, durability and flexibility are crucial for long-term cost-effectiveness. Systems that can monitor large numbers of animals simultaneously are ideal for large-scale research. While increased flexibility may increase costs, it allows researchers to customise setups to meet diverse, long-term experimental needs. Additionally, durable systems with reliable technical support tend to be more cost-effective over time compared to those that require frequent maintenance or offer limited support. Researchers should also consider recurring costs such as software licensing and data storage fees, especially with cloud-based data solutions.

Steps to effectively match an HCM system

A selection guide presented in Figure 2 includes steps to effectively match a HCM system with one's specific needs by considering a number of above-mentioned features. Factors to consider to effectively tailor an HCM system to specific research needs include the behavioural parameters to be monitored, housing requirements, type and volume of data, environmental factors, level of technical support provided, budget, and other specific needs. Additionally, the COST TEATIME HCM catalogue (67) provides a current, validated, and comprehensive overview of available HCM systems. This valuable resource is highly recommended for informed decision-making, as it offers detailed insights into each system's features, technologies, compatibilities, and more.

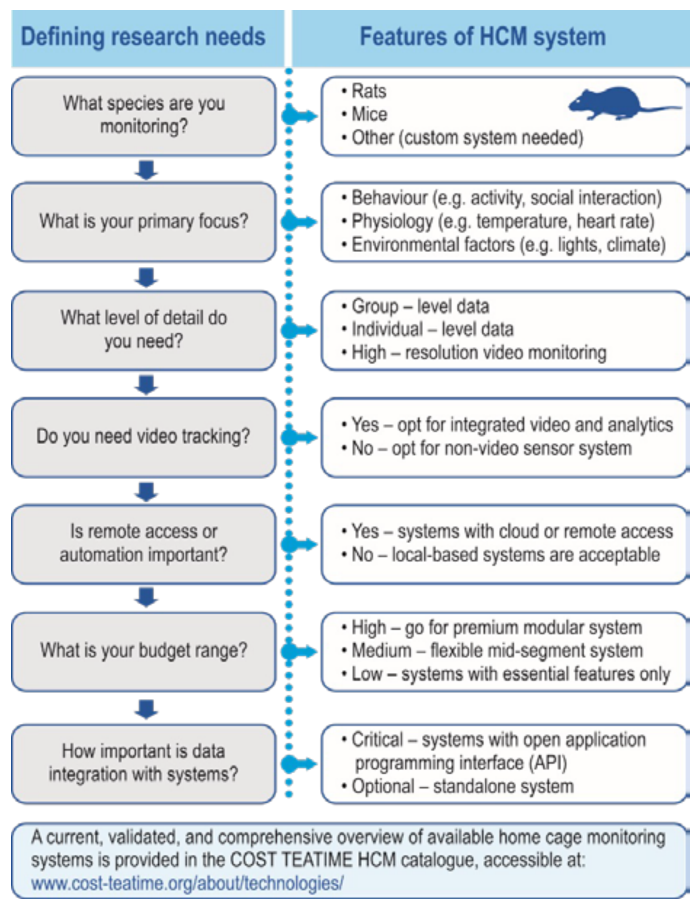

Figure 2: Selection guide for choosing the right HCM system

The dual pillars of HCM success: process and people

The shift from traditional animal assessments to automated HCM systems represents a major change for laboratory personnel. Researchers and staff accustomed to brief and scheduled observations must adapt to continuous, passive data collection. This transition impacts experimental design, duration, and data interpretation (65). Another significant barrier is a lack of standardized training protocols across laboratories.

Without consistent guidelines, data quality can vary, study outcomes may differ between labs, and animal care practices may become inconsistent (68). Moreover, adapting workflows may pose another challenge. Traditional hands-on procedures must be restructured to accommodate automated, around-the-clock monitoring, potentially requiring changes in staff schedules, roles, and facility use (69). Resistance to change can arise, especially from team members comfortable with traditional methods. Nevertheless, successful transitions are achievable when institutions invest in modular training programs, collaborative onboarding, and establish feedback loops between researchers and technical teams (70).

While HCM systems offer clear scientific and ethical advantages such as improved data reliability and enhanced animal welfare, their success ultimately depends not only on the technology but also on effective support for people and processes during the transition (52, 69). Without these, staff may feel overwhelmed or frustrated, slowing adoption and compromising data quality.

Practical challenges in implementing HCM

Setting up HCM systems in laboratory animal research is a complex technical task involving multiple technologies, data challenges, and human factors (13). A primary hurdle is system integration; coordinating hardware such as RFID sensors, infrared beams, and video tracking so they seamlessly communicate with the software (63). For instance, 24/7 automated social behaviour monitoring relies on specialised infrared cameras and intelligent software capable of filtering visual interference from bedding and nesting materials, while adapting to temporal background changes caused by mice building nests or moving bedding (71). Accurate detection of body parts, like the nose and tail base (72), alongside reliable individual identification via RFID, is critical for meaningful data collection (73). When equipment from multiple vendors is combined, compatibility issues and fragmented data systems often arise.

Another major challenge is managing the vast amount of data generated by HCM systems. For example, Digital Ventilated Cages produce about 250 MB of data daily for a rack of 80 cages (19). Researchers must choose between cloud or local storage solutions, balancing scalability, cost, and data security (19). Transitioning from traditional monitoring to HCM also transforms laboratory workflows: researchers accustomed to quick direct observations must adapt to continuous automated data collection, animals require time to acclimate to new cage environments (63, 74), and staff need training to become proficient with new equipment and software.

Despite these challenges, the use of HCM systems is steadily increasing (13). Recent advances in open data-sharing platforms, low-cost devices, and AI-based analysis pipelines are lowering technical barriers, making these systems more accessible to the wider research community (13). Importantly, regulatory agencies are signalling their support for innovative methods that align with the 3Rs. For example, the European Medicines Agency has issued guidelines on the acceptance of 3Rs approaches and continues to explore how novel monitoring technologies can be integrated into regulatory frameworks when supported by strong validation and clearly defined contexts of use (75).

Future perspectives: artificial intelligence in HCM

The substantial data volumes generated by HCM present a significant analytical challenge. To meet this challenge, AI-driven automation can revolutionise HCM by enabling real-time data collection without human intervention. Modern systems leverage automation, machine learning, and predictive modelling to extract relevant data directly from intrinsic environments, overcoming the limitations of direct observation (76). These platforms autonomously track numerous variables, such as animal movement, activity patterns, and physiological changes, that were previously time-consuming and labour-intensive to measure, thereby eliminating human bias and enhancing data reproducibility (Fig. 3) (64).

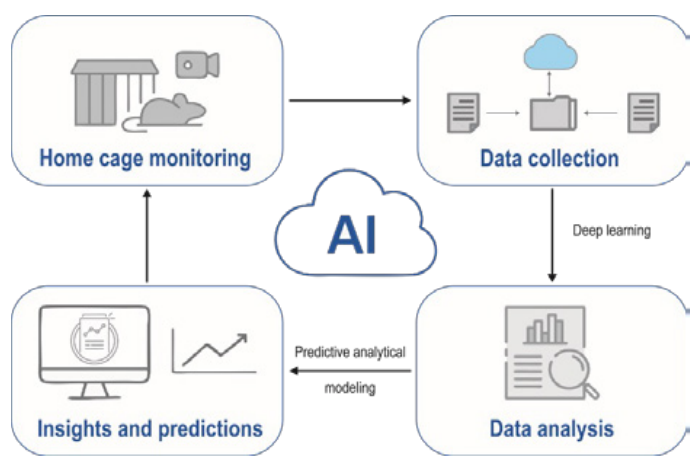

Figure 3: Workflow of an AI-powered HCM system

Contemporary HCM systems utilise deep learning models like ResNet and YOLOv8 to process video feeds and classify behaviours (e.g., grooming, feeding, social interactions) with over 95% accuracy (77). Pose estimation frameworks, such as Social LEAP Estimates Animal Poses, detect subtle movements like limb kinematics and facial expressions, aiding in the early identification of neurological disorders (78). Furthermore, self-supervised learning reduces dependence on manually annotated datasets, making large-scale behavioural studies more practical (79).

Predictive analytical modelling uses historical behavioural data to forecast events, such as disease progression, stress responses, or abnormal activities. Large datasets feed AI algorithms that can detect early behavioural abnormalities that are indicative of subclinical health issues. For instance, random forest classifiers analysing mouse trajectories and body postures achieved over 80% accuracy in cognitive and behavioural phenotyping, outperforming traditional measures and improving models of neurodegenerative disorders (56). Deep learning, a branch of machine learning, also enhances HCM by integrating multi-modal data streams, including video, audio, and biometric sensors. Ivanenko et al. (2020) demonstrated that deep learning models could classify mouse sex and strain based on ultrasonic vocalisations, achieving 77 % accuracy in sex determination (80).

Despite these advances, AI integration in HCM faces ethical and practical challenges. Algorithms trained on small or biased datasets, often limited to one strain or sex, may lack generalisability (81). Moreover, transparency in AI methods and data privacy concerns, particularly in longitudinal animal studies, require strict regulation (82). Fuochi et al. (2024) emphasised the value of big data generated by HCM systems, showing how repurposing these datasets can reduce the need for additional animal experiments, thus supporting the 3Rs principle in animal research (19). Through automation, predictive analytics, and deep learning, AI is transforming HCM into a smarter, faster, and more humane scientific tool.

HCM in low-income countries: barriers and opportunities

A key obstacle for the adoption of HCM is the technical expertise required to operate these advanced systems. Modern HCM platforms, such as the Digital *In Vivo* System, demand specialised skills in hardware and sensor development, data management, machine vision, and behavioural analysis (83). Many research institutions lack access to such experts, which can hinder effective system use. Although online training courses exist for various HCM systems, most are tied to paid care plans, limiting accessibility for researchers in low-income countries, when institutional financial support for HCM maintenance and training is unavailable. Additionally, in-person comprehensive training programs or certified courses for researchers and technicians remain scarce. Another challenge lies in managing the vast volumes of data generated by continuous 24/7 monitoring, which demands robust infrastructure for storage, processing, and analysis, resources that may exceed the capabilities of many laboratories. Therefore, there is a current need for capacity building through personnel training and hands-on experience to effectively operate and escalate the use of such systems in low-income countries, eventually promoting effective 3R practices.

Conclusions

HCM systems are gaining importance in a landscape of increasing demand for ethical and high-quality animal research, as they enable continuous, automated data collection that strengthens both scientific accuracy and animal welfare. By promoting Refinement, while offering avenues for Reduction and partial Replacement of animal use, they are emerging as pivotal tools in advancing the ethical framework of the 3Rs in animal research. Recent advances in AI-driven tools, such as machine learning, have the potential to improve the collection and analysis of behaviour and health monitoring data in laboratory animals, making studies more accurate and sensitive. However, successful adoption requires careful system selection, staff training and sound data management, with particular attention in resource-constrained environments. Nevertheless, supported by regulatory momentum and a growing scientific evidence base, HCM systems have the potential to be recognised not only as a valuable research tool but also as a method that advances both scientific quality and animal welfare.

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Pametne kletke, večja dobrobit: Podpora načelom 3R v raziskavah na živalih s spremljanjem v domači kletki in ustrezno izbiro sistema

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Izvleček: Visoki standardi dobrobiti živali v raziskavah niso zgolj etična obveznost, temveč tudi temelj visokokakovostne znanosti. Raziskovalci lahko izboljšajo tako dobrobit živali kot tudi zanesljivost podatkov z uvedbo strategij, ki zmanjšujejo stres pri poskusnih živalih. Eden izmed sodobnih in učinkovitih pristopov je spremljanje živali v njihovem domačem okolju. Sistemi za spremljanje v domači kletki (HCM, angl. *home-cage monitoring*) združujejo več pristopov za samodejno, neprekinjeno in neinvazivno spremljanje fiziologije in vedenja laboratorijskih živali v njihovem domačem okolju. HCM podpira naravne ritme in vedenja živali ter zmanjšuje stres iz različnih virov in potrebo po posegih človeka. V članku opisujemo, kako HCM prispeva k načelom 3R, ki sta ga uvedla Russell in Burch, s posebnim poudarkom na izbiri najprimernejšega sistema HCM za specifične raziskovalne potrebe. Obravnavamo razpoložljive vire in praktične omejitve pri izviri sistema ter podajamo kratek pogled na razvijajočo se vlogo umetne inteligence pri analizi podatkov HCM. Prispevek obravnava tudi priložnosti in ovire pri uvajanju HCM, zlasti v povezavi z državami z manj razvito raziskovalno infrastrukturo in omejenimi sredstvi v Evropi. Naše osrednje sporočilo je jasno: uporaba tehnologij HCM podpira načela 3R ter spodbuja boljšo dobrobit živali in boljšo znanost.

Ključne besede: laboratorijske živali; avtomatsko spremljanje vedenja; izboljšave; kontinuirno zbiranje podatkov; stres