Robotic herding framework design for remote and small-scale pastoral farming

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Abstract: This study presents a comprehensive framework for designing an intelligent and sustainable robot-assisted herding system, based on a systematic literature review and field investigations conducted in remote pastoral regions operated by small family farms. The study highlights a multi-institutional collaboration between the EUREKA Robotics Centre, Cardiff Metropolitan University, UK; Universiti Malaysia Kelantan; and Shenyang University of Technology, China. The research aims to ensure that advancements in robotic technology are effectively aligned with the practical challenges encountered in livestock herding. The literature review reveals that robotic-assisted herding has evolved from theory to early practical applications through advances in AI, robotics, and agriculture. The study conducted a field survey involving fifty-five farmers, and it revealed low initial awareness from the farmers but high practical acceptance of robotic herding solutions, and challenges in costing and cultural shift. To overcome these challenges, the study applied the integration of object-oriented robotic design with educational initiatives customized to local herding environments. It also coordinated with stakeholders such as farmers, robotic innovators, and local authorities in robotic herding. The proposed framework prioritizes modularity, durability, and adaptability to local context in the robotic design. Future work will focus on iterative development and field trials across China, Malaysia, and the UK. This study is intended to validate and refine the framework. This effort will contribute to global precision livestock farming and the broader transformation toward sustainable agriculture.

Keywords: smart agriculture, small family farm, herding, animal welfare, interdisciplinary robotics research
DOI: 10.25165/j.ijabe.20251806.9826

Citation: Liu J Y, Chew E, Sia C S, Adli H K, Zhang L N, Gai S C, et al. Robotic herding framework design for remote and small-scale pastoral farming. Int J Agric & Biol Eng, 2025; 18(6): 182–190.

1 Introduction

1.1 Background of smart agriculture and small family farms

Smart agriculture, characterized by Agriculture 4.0, integrates big data, machine learning, deep learning, generative adversarial networks, swarm intelligence, blockchain, cloud-fog computing, robotics, autonomous systems, the IoT, and cyber-physical systems[1-3]. Precision Livestock Farming (PLF), a subset of smart agriculture, uses Radio Frequency Identification (RFID) tags, walk-in weighing platforms, Global Positioning System (GPS), drones, satellite remote sensing, and sensors[4]. These tools are employed to facilitate real-time monitoring, personalized care, and precise pasture management[4-6]. Robotics and Artificial Intelligence (AI) offer significant potential by automating labor-intensive tasks, boosting productivity, optimizing animal welfare, and addressing rural labor shortages[7-9]. The convergence of engineering, computer science, and animal husbandry promotes transformative innovations in livestock practices[10]. However, the majority of research remains theoretical and has yet to be implemented on a larger scale, with no comprehensive framework established to integrate human–robot–animal interactions. This gap underscores the need for a collaborative and global perspective to drive practical and sustainable solutions[11,12]. This study provides an initial insight into integrating robotics with traditional herding, highlighting the need for pilot trials, farmer engagement, and interdisciplinary collaboration to develop responsible, scalable, and welfare-centered robotic livestock. Small family farms, historically fundamental to global agriculture, are managed primarily by family members who control key resource and livestock decisions[13-15]. About 90 percent of the world's 570 million farms fall under this category[13,16]. These family farms are typically located in remote or semi-remote rural areas, often characterized by limited infrastructure, restricted access to digital technologies, and dependence on traditional herding and crop management practices[17]. These family farms play pivotal roles in ensuring food security, mitigating rural depopulation, and

Received date: 2025-04-04 **Accepted date:** 2025-09-14
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preserving culture. Yet they face significant challenges, including geographical isolation, outdated infrastructure, and limited access to updated agricultural information[18]. Their limited scale and economic restrictions often hinder competitiveness[18]. The study proposes that adopting digital and robotic technologies can enhance productivity and competitiveness. The study also examined specific barriers faced by small-scale herding operations, including farmer attitudes, operational needs, and ethical considerations. Addressing these challenges is crucial for this study to inform the effective integration of Robotics and AI technologies in sustaining small family farms.

1.2 Research objectives and significance

This study investigates livestock management practices in remote mountainous pastoral areas composed of small family farms in regions between 32°N-46°N latitude and 105°E-130°E. It focuses on the farmers' and prospective farmers' awareness and acceptance of herding robots. However, the effectiveness of robotic system design depends on users' cognitive frameworks and specific requirements, highlighting the importance of understanding farmers' perspectives. The study seeks to find answers to the following questions: 1) What traditional livestock management practices are currently employed by farmers on small family farms, and what types of external support do they require? 2) To what extent are farmers and prospective farmers aware of livestock robotic technologies, and what are their attitudes and willingness to adopt these technologies? 3) How are global research trends evolving, and how can interdisciplinary collaborations be leveraged in the application of robotics and AI in livestock farming? Addressing these questions will identify farmers' technology-related needs and barriers to technology adoption. This understanding will inform the development of livestock robotic systems tailored to the specific needs of small family farms.

2 Systematic literature review

The study employed a Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)-based systematic review[19] to conduct a literature search across two primary databases: Scopus and Web of Science[20,21]. The following keywords were used: "Robotics Herding", "robotics grazing", "smart herding", "smart grazing", "Intelligent herding", "Intelligent grazing", "intelligent animal husbandry", and "robot animal husbandry". This review comprised Agricultural and Biological Sciences and Computer Science and Engineering[22], excluding literature from unrelated disciplines.

All collected articles underwent two rounds of deduplication to eliminate overlapping records from Scopus and Web of Science. This step is to ensure that each study is recorded once[20,21]. A further screening was applied to exclude non-peer-reviewed publications, including conference papers, newsletters, and editorial clips. Only peer-reviewed journal articles were retained to ensure robustness of the review. Titles and abstracts were screened through semantic analysis to identify articles that focused specifically on robot-assisted herding, including drones, autonomous ground vehicles, and AI-based livestock monitoring systems. Articles unrelated to livestock, such as crop automation or Artificial General Intelligence, were excluded. Systematic and narrative review articles were also excluded to avoid secondary citation bias and to focus solely on original empirical studies. The final set of articles was critically appraised to ensure methodological soundness, validity, and practical relevance[19]. Finally, the articles that met high-quality benchmarks were included in the core analysis, whereas lower-quality but contextually relevant articles were retained for reference purposes[23], as shown in Figure 1.

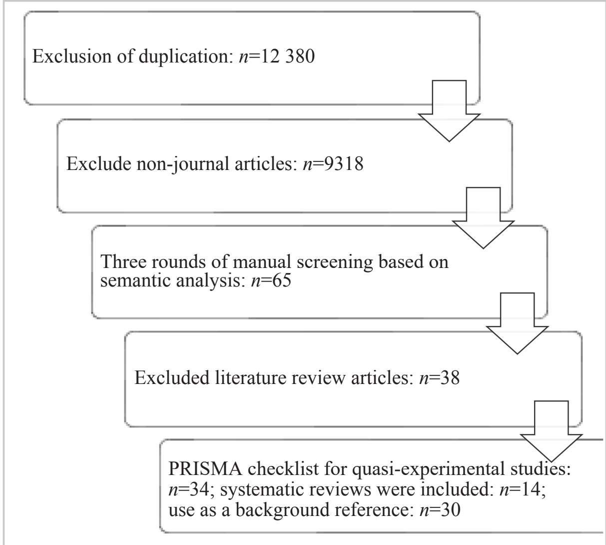

Figure 1 Flow diagram of the literature screening process

2.1 Bibliometric profiling

Research on robotic herding remains in its early developmental stage, with most publications appearing between 2017 and 2024 and focusing primarily on conceptual and experimental validation rather than large-scale implementation. The earliest work by Drach et al.[24] explored automation in livestock management through robotic milking, demonstrating labor reduction and productivity improvement but lacking autonomous behavioral control. In 2018, Nardi et al. and Paranjape et al. introduced game-theoretic multi-robot coordination and UAV-based flock guidance, establishing the theoretical groundwork for multi-agent herding systems[25,26]. In 2021, the research studies were mainly focused on the mean-field control frameworks for swarm coordination[27] and LoRa-enabled drone communication systems for rural monitoring[28]. In 2022, the research studies expanded to a wider range of approaches, including occlusion-aware coordination, acoustic-driven herding, and vision-based predator detection modules[29-31]. Recent studies (2023-2024) demonstrated incremental progress toward practical validation, including small-scale field experiments with cattle[32] and the emergence of distributed control algorithms and open datasets[33,34]. Figure 2 illustrates the number of publications in herding from 2017 to 2024.

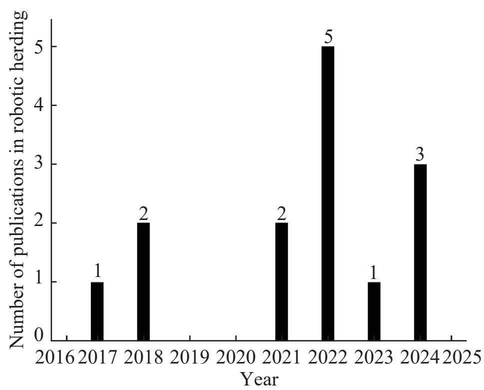

Figure 2 Number of publications in robotic herding (2017-2024)

Robotic herding has emerged as a globally recognized yet domain-concentrated research field, marked by cross-continental participation but limited methodological maturity. Between 2017 and 2024, representative studies have been published across nine countries—China (CN), the United States (US), Spain (ES), Japan (JP), Italy (IT), Israel (IL), Malaysia (MY), the United Kingdom (GB), and Australia (AU), illustrating the worldwide recognition of robotic herding as a component of intelligent and sustainable agriculture[24-37]. Table 1 lists the global distribution of research on robot-assisted herding.

Table 1 Global distribution of robotic herding research by country

Country	CN	US	ES	JP	IT	IL	MY	GB	AU
Number of publications	3	2	2	2	1	1	1	1	1

2.2 Thematic trends in robotic herding

Research on robotic and AI-assisted livestock management indicates a pragmatic division of aims: while single-agent systems are mainly employed for behavioral testing, controllability analysis, and welfare-aware pilot trials, multi-robot coordination proves more effective for accomplishing large-scale herding tasks that demand greater spatial coverage, robustness, and adaptability to fragmentation or occlusion[25,29,30,33,35,36]. Studies confirm that decentralized and game-theoretic algorithms enable cooperative management of herding dynamics while maintaining global convergence[25,36]. Multi-stage pursuit-encirclement-guidance frameworks enhance adaptability in non-cooperative target scenarios[36], whereas mean-field and occlusion-based approaches strengthen controllability, stability, and motion efficiency in complex environments[27,29].

Perception research has simultaneously advanced from static sensing to multimodal and real-time recognition of animals and environmental conditions. Integrated datasets combining RGB, depth, and behavioral labels have enabled object-detection models capable of accurately identifying livestock, predators, and humans[31,34]. Real-time vision systems achieving up to 64 FPS support adaptive decision-making in dynamic environments[31], while fiducial marker-based localization and sensor fusion approaches improve spatial precision for both structured barns and open pastures[37].

Effective communication technologies further support large-scale, distributed herding systems. UAV-based wide-area LoRa networks have achieved communication ranges up to 10 km, while optimized flight paths reduce data-collection time by more than 70%[28,37]. Synchronized data exchange between robots and cloud servers ensures consistent command execution and reliable feedback[36,37], confirming the feasibility of a cloud-edge-device collaborative system.

Behavioral and field experiments have identified unmanned aerial vehicles (UAVs) as the most efficient and flexible robotic agents for autonomous herding. UAVs enable rapid aggregation and directional steering of livestock with high precision across large spatial ranges[32,35]. Although repeated operations can induce habituation, adaptive flight strategies—adjusting altitude, approach angle, and acoustic stimuli—maintain responsiveness and minimize stress[30,32]. In contrast, ground vehicles face limitations in maneuverability and responsiveness on uneven terrain[35]. These findings confirm UAVs as the primary operational platform integrating sensing, control, and communication for efficient and welfare-compliant herding.

Economic and welfare assessments reinforce the overall value of robotic herding. Long-term deployments indicate that automation can reduce human labor by up to 80% and increase milking frequency by 45.5%, significantly improving productivity and cost efficiency[24,29]. From an ethical perspective, automation also supports animal welfare: optimized flight distances, reduced noise levels, and adaptive behavioral models lessen stress responses in livestock[32,35].

Integrating physiological and behavioral monitoring into UAV systems provides quantifiable welfare data, ensuring compliance with welfare standards while maintaining operational efficiency. Consequently, UAV-centered herding aligns with the global trend toward ethical, welfare-driven, and sustainable smart farming. Despite these advancements in control, perception, communication, execution, and welfare[24,28-30,32-34], a key integration gap remains: no existing study has established a complete human-robot-animal feedback loop connecting task assignment, autonomous decision-making, and real-time response. Bridging this gap will require unified frameworks that integrate human operators, cloud-based intelligence, and UAV agents within a continuous decision-action-feedback cycle—laying the groundwork for scientifically verifiable, welfare-oriented, and economically sustainable herding ecosystems.

2.3 Roles of stakeholders in smart herding technology adoption

Building upon the previous literature review on robotic-assisted herding, this section conducts a stakeholder analysis to further explore the complex interactions among technological, human, and institutional actors that influence the development and implementation of such systems[12,30,32,35,36].

Figure 3 depicts a triangular interaction loop that fundamentally defines the main players in robot-assisted herding activities. Farmers supervise and control robots, ensuring their performance aligns with practical needs and ethical standards[4,24]. Robots, in turn, provide farmers with data and efficiency gains, facilitating better decision-making and labor reduction[28,30]. Farmers maintain the care and welfare of animals, while animals communicate responses and signals that reflect their behavior and well-being[8,32]. A two-way process of guidance and behavioral feedback between robots and animals enables adaptive control of robot-assisted herding systems[29,33,36].

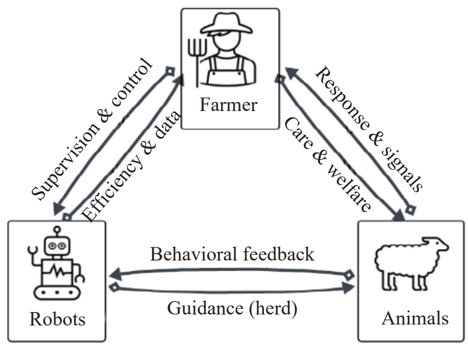

Figure 3 Core stakeholders for smart herding technology

Figure 4 extends the analysis to the macro-level institutional ecosystem, involving local authorities, funding institutions, researchers, suppliers, and farmers. Each stakeholder plays a distinct but interdependent role in facilitating the development and dissemination of robotic herding technology[38,39]. Local authorities provide subsidies, policy support, and training while integrating adoption feedback into future agricultural strategies[39-41]. Financial institutions offer funding, loans, and leasing mechanisms that enable technological investment and risk management[14,41]. Researchers contribute technological innovation, field validation, and policy evidence[33,34,36]. Suppliers deliver robotic systems and receive user feedback to refine their products[37,42]. Farmers serve as the central link, connecting scientific, financial, industrial, and policy frameworks through their practical experience and operational feedback[5,15,16]. The diagram illustrates a comprehensive collaboration model that supports technological advancement through multi-directional communication and mutual reinforcement[3,9].

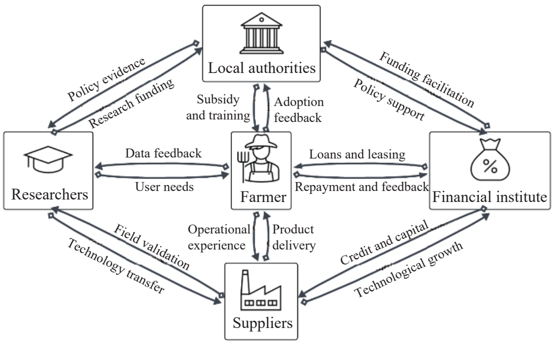

Figure 4 Support network for smart herding technology

Based on Figures 3 and 4, the success of robotic-assisted herding relies on both technological capability and collective stakeholder engagement. It is therefore recommended that future initiatives should reinforce multi-stakeholder collaboration, align innovation with practical needs, and establish supportive policies that promote sustainable and inclusive agricultural transformation[4,9,32,39].

3 Empirical study

3.1 Data collection and research methods

An empirical study was conducted in a pastoral village composed mainly of small family farms, with approximately 600 households and a total population of around 2400 to 2800 residents. More than 300 households owned livestock and relied primarily on small-scale mixed farming for their livelihoods. The average household consisted of 3 to 5 members, and annual household incomes ranged from USD 6000 to 8000, depending on herd size and seasonal agricultural output. The village's economic structure and environmental setting represented the typical characteristics of pastoral communities in the region between 32° and 46° north latitude and 105° and 130° east longitude. In this region, livestock production is primarily based on grassland grazing, characterized by mixed-species herding, high grazing intensity, and concurrent grassland degradation, with fragile ecosystems highly sensitive to climatic variability[43].

A mixed-method research approach was adopted to gain a comprehensive understanding of local ecological conditions, livestock practices, and farmer perceptions of robotic technologies[44,45]. Quantitative data were collected through paper-based questionnaires distributed in a pastoral village composed mainly of small family farms. 55 households with livestock (18% of all households) participated in the survey, with one representative from each household completing a paper-based questionnaire. The questionnaire included both multiple-choice and open-ended items that examined farmers' traditional herding methods as well as their awareness, acceptance, and interest in mobile robotics[46-50].

Qualitative data were collected through semi-structured interviews with two selected key informants[44,51]. Each 30-minute interview took place in quiet outdoor settings. A written consent was obtained before the interviews[52]. The first respondent was a village leader (A1, male, 43), who provided an overview of community farming practices, including information about village demographics, land allocation patterns, and local environmental characteristics that shape agricultural and pastoral livelihoods. The second respondent was a farmer from a small family farm (A2, male, 47), who offered practical insights into traditional herding routines, including sheep breeding and feeding practices, seasonal grazing routes, and daily herding management based on inherited local knowledge.

3.2 Farmers' attitudes toward traditional grazing

Figure 4 shows respondents' views about traditional herding practices. Each column represented a statement, and the vertical axis showed the percentage of respondents at each level of agreement. The bubble colors represent different levels of agreement among respondents: cyan indicates "strongly agree", blue indicates "agree", red indicates "neutral", orange indicates "disagree", and green indicates "strongly disagree". The vertical position of each bubble corresponds to the percentage of responses[46,47].

The survey results reveal multiple dimensions of challenge embedded in traditional herding practices, reflecting both operational and structural constraints within the livestock sector. Among 55 respondents, 76.4% agreed or strongly agreed that traditional grazing methods face labor shortages, confirming that the decline of rural labor supply is a critical issue shaping livestock productivity. 43.6% of participants agreed that traditional methods restrict the overall development of the livestock industry, while 30.9% disagreed and 25.5% remained neutral. This divergence suggests that although a substantial portion of farmers recognized efficiency limitations, others continue to view traditional practices as sustainable and culturally embedded systems.

Economic considerations also influence farmers' perspectives. A large majority (81.8%) believed that adopting alternative livestock practices could enhance economic income, and 78.2% expressed willingness to modify current methods. In addition, 80% agreed that traditional grazing requires improvement or innovation, indicating widespread openness to reform when it brings tangible benefits. A cultural identity remains a significant moderating factor, where 41.8% agreed that traditional methods should be preserved for their cultural value, 34.5% disagreed, and none strongly agreed. The high variability implies that while most respondents prioritize innovation, a portion still attaches symbolic value to pastoral traditions (Figure 5).

3.3 Farmers' attitudes toward robotic herding

The heatmap (Figure 6) depicts farmers' attitudes toward the use of herding robots. Only 14.5% of respondents considered themselves familiar with the concept and applications of robotics, while the majority (74.5%) selected lower to mid-scale responses. This limited awareness suggests that although interest in innovation exists, exposure to robotic technologies within rural contexts is still limited. 69.1% agreed that robotic technology is suitable for application in the livestock sector, and 70.9% believed it could improve work efficiency, demonstrating strong confidence regarding its operational potential. 81.8% agreed and strongly agreed that robots could help reduce physical labor demands.

52.7% of respondents agreed that robotics could enhance animal welfare, while 72.7% believed it could improve working conditions and living standards. 67.3% anticipated that the introduction of robots would affect traditional grazing practices, while 38.2% raised concern that robotic technology adoption might cause unemployment among farmers. Training and technical support were recognized as critical conditions for adoption, where 78.2% agreed that training would be necessary, and 60% were willing to participate. 67.3% agreed that robots might impose an economic burden, suggesting that affordability, rather than resistance, is the key constraint.

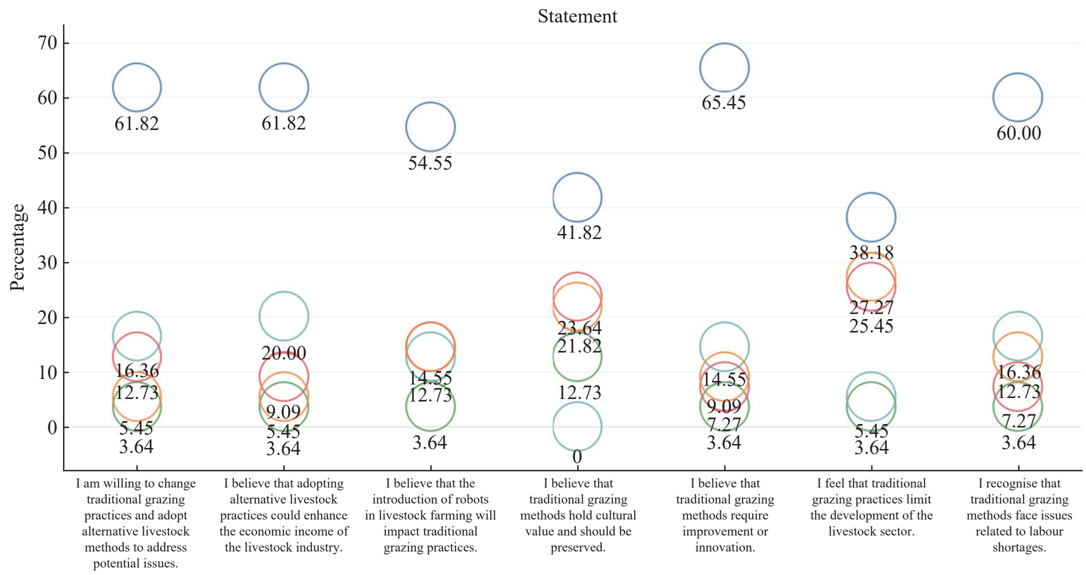

Figure 5 Farmers' attitudes toward traditional grazing

Question	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
I am concerned that the use of robots in livestock farming could lead to unemployment among farmers.	14.55%	21.82%	30.91%	27.27%	5.45%
I am familiar with the concept and applications of robotics.	10.91%	34.55%	40.00%	9.09%	5.45%
I am willing to undergo training related to the use of robots on my individual farm.	5.45%	18.18%	16.36%	47.27%	12.73%
I believe that implementing robots in the livestock industry can enhance animal welfare.	0%	20.00%	27.27%	45.45%	7.27%
I believe that robotic technology is suitable for application in the livestock sector.	1.82%	9.09%	20.00%	56.36%	12.73%
I believe that technical training will be necessary for the application of robots in livestock farming.	0%	7.27%	14.55%	40.00%	38.18%
I believe that the introduction of robots in livestock farming will impact traditional grazing practices.	3.64%	14.55%	14.55%	54.55%	12.73%
I feel that using robots in livestock farming may impose an economic burden on individual farmers and ranchers.	3.64%	18.18%	10.91%	43.64%	23.64%
I think that using robots in livestock farming can improve work efficiency.	3.64%	12.73%	12.73%	52.73%	18.18%
I think that using robots in livestock farming will improve working conditions and living standards.	1.82%	1.82%	23.64%	60.00%	12.73%
I wonder whether using robots in livestock farming can alleviate physical labour.	3.64%	5.45%	9.09%	58.18%	23.64%

Figure 6 Heatmap of farmers' attitudes toward herding robot statements by tableau

3.4 Discussion of findings

Traditional herding, though deeply rooted in culture and identity, is increasingly constrained by demographic decline, labor shortages, and the physical demands of livestock management—particularly as rural populations age, youth participation declines, and large herds must be managed across vast and complex terrains (see Section 3.2). These challenges indicate that traditional labor-dependent models may no longer sustain the productivity and resilience required under changing social and environmental conditions. Moreover, traditional herding lacks the capacity for continuous surveillance, precision control, and real-time animal health management. These capabilities are essential for maintaining efficiency, safety, and welfare in modern livestock operations. Robotic assistance, therefore, emerges as a practical response to the structural decline of the traditional system. It can perform repetitive or high-risk tasks, provide continuous environmental and behavioral monitoring, and operate across terrains and time spans inaccessible to humans[4,6,7,12,38,42]. Through automation and intelligent sensing, robots can introduce a data-driven dimension to herding, enabling early detection of animal health issues, optimization of grazing patterns, and more sustainable land use[4,7,8,53]. Robotic herding does not aim to replace human herders but to support them, allowing herders to focus on decision-making, animal welfare, and cultural transmission while offloading physical burdens to machines[38,42]. From a theoretical standpoint, this shift represents a sociotechnical adaptation process, where innovation evolves within, rather than against, traditional approaches[38,54]. The automation in agriculture can be accomplished when it aligns with local social structures and community values[54]. Schnack et al. highlight that sustainable technological adoption requires co-adaptation between human agency and technical efficiency[55]. In this context, the use of robots in herding embodies a balanced path forward, bridging cultural preservation and modern efficiency. It ensures that pastoral knowledge evolves in tandem with technological progress, supporting both the preservation of traditional practices and the advancement of sustainable livestock production.

3.5 Insights from traditional herding practices

According to A1, traditional livestock farming in this region typically involved integrated agricultural-livestock systems. Farmers primarily raised sheep (about 70% of livestock), along with cattle and pigs. They benefited economically from hybrid breeds such as Australian White and Small-tailed Han sheep, which were known for improved growth, disease resistance, and higher meat yields. According to A2, herd management methods could be extensive. Traditional grazing techniques, such as leading, driving, carrying, and waiting, to optimize pasture usage and prevent land degradation were adapted seasonally and geographically. In adverse weather, sheep were managed in pens with supplementary feed, and sheepdogs assisted farmers in daily management. Sheep clustering varied according to pasture conditions, with techniques such as horizontal formation, dispersed pattern, and column-like formations. By digitally mapping traditional grazing routes and seasonal pasture conditions, robots could effectively guide sheep to form these traditional herd formations. This ensures efficient pasture utilization. Robots enhanced with AI-driven sensors and algorithms can emulate experienced shepherds' observational skills and can detect abnormal animal behaviors or health issues early[7,8]. Incorporating traditional auditory cues such as vocal commands, whistle signals, or bell tones can engage animals' innate behavioral responses, thereby reducing stress and promoting improved animal welfare outcomes[12,35]. A robotic herding system can be used to monitor livestock and can improve livestock management efficiency[26,31]. Robotic herding design considers local cultural practices, such as traditional livestock knowledge passed down from generation to generation. This cultural integration can help the system to gain wider acceptance and become more sustainable in traditional livestock communities[48].

4 Proposed intelligent robotic unmanned aerial vehicles (UAVs) herding framework

Based on the integration gap identified in the literature, this study proposes a unified human–robot–animal framework that establishes a continuous perception–decision–control cycle for intelligent livestock herding. The framework connects human supervision, onboard intelligence, and autonomous UAV agents within an adaptive coordination structure. In this configuration, UAVs serve as the primary operational entities, equipped with algorithm-driven perception systems, multimodal sensors, and real-time communication links to ensure welfare-oriented guidance and efficient herding performance.

Figure 7 illustrates the operational structure of the proposed framework within a small family farm context. The system forms a closed-loop interaction among the ranch, control center, and UAV operational units. At the ranch level, a fleet of UAVs conducts herding operations by observing, monitoring, and guiding livestock between home enclosures and grazing zones. Each UAV continuously collects behavioral and positional data, which are processed by the onboard computer to support real-time perception, situational analysis, and path optimization. The onboard processor integrates visual and radar information to enable obstacle avoidance, group coordination, and adaptive control before transmitting commands to the flight controller.

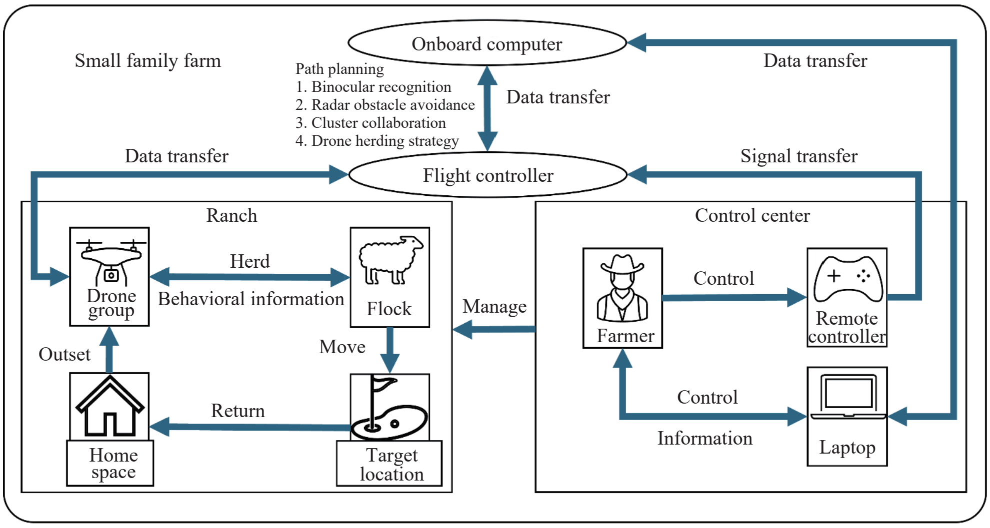

Figure 7 Robot-assisted herding framework

The control center integrates the farmer, remote controller, and laptop interface. Farmers monitor operations through real-time visualization dashboards and can manually intervene when necessary. Continuous information exchange between livestock, UAVs, and the human operator completes the perception–decision–communication–control loop. This integrated design links human management, robotic execution, and animal behavior in a dynamic and adaptive process—achieving intelligent, welfare-driven, and cost-efficient herding particularly suitable for small family farms with limited labor resources.

5 Preliminary pilot simulation based on animal behavior

To demonstrate the feasibility of the proposed human–robot–animal framework, a series of simulations was conducted to visualize UAV-assisted herding behaviors and control mechanisms.

Figure 8 shows an initial path-planning simulation showing the coordinated movement of a drone and a sheep herd in a dynamic environment with multiple obstacles. The red curve represents the UAV's trajectory, which adapts to terrain constraints as it moves from left to right to influence the herd's movement. The black curve shows the sheep cluster's corresponding trajectory, progressively shifting toward the target area under UAV guidance. The green dots simulate static obstacles scattered across the field, representing irregular terrain such as bushes or rocks. Both UAV and herd trajectories demonstrate obstacle avoidance and smooth coordination, validating the system's capability for real-time path planning and behavioral adaptation. The drone performs oscillatory maneuvers to maintain optimal spacing and apply gradient-based repulsive influence, ensuring efficient control while minimizing animal stress. This preliminary simulation visually verifies the spatial coordination and obstacle-avoidance logic embedded in the framework's path-planning algorithm.

Figure 9 presents a simulation model of how autonomous UAVs can be navigated to assist sheep herding. The drones are represented by three colored dots, i.e., blue, pink, and purple, respectively. The numerous green dots on the right side of the diagram indicate a cluster of sheep. The presence of red dots within the dense cluster of green dots represents the herd leader (head sheep), which exerts a guiding effect on other sheep. The green boundary delineates the dynamic of the sheep cluster. The target zone, illustrated by red concentric circles, indicates the desired destination of the herd.

In the beginning, the drones were deployed around the outer perimeter of the herd. Each drone exerted a repulsive influence on all sheep within its effective range of interaction. The strength of this repulsion decreased with distance, forming a gradient pressure that guided the herd's collective movement without physical contact[11,29]. Instead of targeting individual sheep, the drones guide the collective spatial distribution and density of the herd, indirectly steering towards the herd leader, which in turn attracts the remaining sheep through an inherent following behavior.

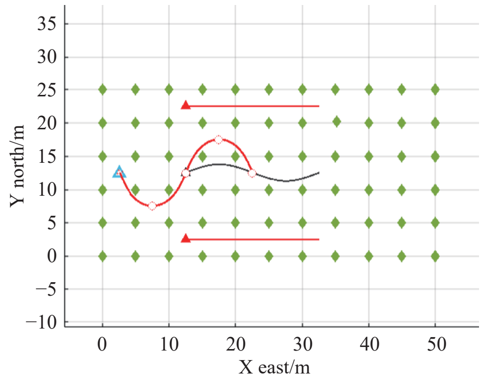

Figure 8 Concept diagram of drone-simulated herding

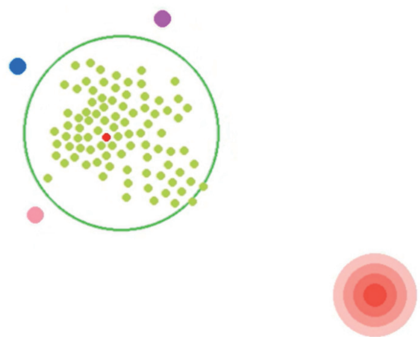

Figure 9 Simulation of drone herding on animal behavior

If the herd became widely dispersed, the nearest drone switched to Orbit Mode, circling the cluster and applying distributed repulsion around its perimeter to compress the herd density and restore cohesion[33]. Once the sheep cluster was assembled, the drones transitioned to Drive Mode and positioned behind the herd to maintain directional repulsive pressure to navigate the cluster along an arc-shaped trajectory toward the target zone[36].

If the herd density increased excessively, the drones shifted to Control Mode, retreating slightly to reduce local repulsion intensity and avoid over-compression. This would allow the herd to relax while preserving spatial coherence[32]. Through this process, repulsion from drones and attraction to the herd leader jointly shaped the collective motion, achieving adaptive and humane navigation through a distance-decayed field-based control mechanism.

6 Limitations and future work

This study offers preliminary insights into integrating robotics with traditional herding practices and assessing farmers' acceptance of robotics herding. The survey was based on a sample of fifty-five participants, who consisted of local farmers engaged in small-scale livestock herding from a single village in China. In addition, two experienced herders were interviewed to provide qualitative insights into their perceptions of robotic herding. This study was restricted by its geographical limitation, which constrains the generalizability of findings across regions with diverse cultural and economic conditions. Data collection was conducted as a single cross-sectional study. Consequently, this represents a challenge in assessing the longitudinal effectiveness and economic benefits of robotics in livestock farming.

Future work will prioritize the integration of existing sensing, decision-making, communication, and control modules into the proposed human–robot–animal UAV-assisted herding framework. The next phase will focus on implementing small-scale pilot field trials to evaluate the framework's technical feasibility, adaptability, and welfare compliance under real herding conditions. These trials will enable iterative refinement of system parameters and interaction strategies through continuous feedback from both farmers and livestock behavioral responses. Technical advancements such as multi-agent reinforcement learning, pasture rotation planning, and real-time livestock stress monitoring can be implemented to strengthen UAV-based livestock systems. Consequently, a "responsibility by design" approach is recommended to consider impacts on future work structures, human well-being, and farming systems[9,56]. Strong collaboration between technologists, agricultural experts, and animal welfare practitioners is essential to balance efficiency with sustainability. Local authorities can further support innovation through incentives, regulation, and partnerships[39]. Best practices with an open-source agricultural robotics platform could strengthen interdisciplinary research collaboration and accelerate progress by facilitating dataset sharing, benchmarking, and broader adoption of established methodologies[31,34].

7 Conclusions

This study establishes an initial and pivotal understanding of the development of intelligent and sustainable herding systems, offering a critical insight for the integration of robotics and AI in livestock management. It begins with a systematic literature review[20,21] alongside empirical field investigations in robotics herding[13,14]. While traditional livestock practices remain prevalent in remote regions, farmers showed a strong openness to robotic herding technologies for the perceived practical benefits. Successful adoption depends on improving awareness, reducing costs, providing training, and integrating innovations that assimilate local cultural values. The study highlights the critical importance of incorporating stakeholders, including farmers, technologists, and local authorities. This collaboration is needed to build a sustainable ecosystem for the responsible and effective deployment of the smart herding solutions. This study proposes a modular UAV-based robotic herding framework that integrates AI-driven perception, adaptive control algorithms, and human-supervised interfaces. The framework emphasizes human–robot–animal coordination to ensure scalability, real-time adaptability, and alignment with local herding practices for small-scale pastoralists. This study contributes to bridging the gap between technological innovation and practical implementation in livestock systems by offering a pathway toward inclusive, resilient, and sustainable agricultural development.

Acknowledgements

This work was supported by technical equipment provided by the EUREKA Robotics Centre at Cardiff Metropolitan University, with venue support provided by the Rural Workgroup of Shenyang University of Technology.

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