Companion Animal Emotion and Health Status Monitoring Based on Wearable Multimodal Sensing

Yibo Meng *
Tsinghua University
Beijing, China
mengyb22@mails.tsinghua.edu.cn

Ziyuan Qu *
Rmit University
Melbourne, Australia
s4087188@student.rmit.edu.au

Yan Guan
Tsinghua University
Beijing, China
guany@tsinghua.edu.cn

Abstract

The emotional state of companion animals (such as dogs) is closely related to their health and well-being, but traditional evaluation methods rely on subjective observation and lack objective quantification methods. This paper proposes a non-invasive monitoring system based on multimodal wearable sensing. By collecting skin electrodermal activity (EDA), photoplethysmography (PPG), inertial measurement unit (IMU) and sound data, combined with machine learning methods, it can realize the automatic recognition of canine emotional state. Experimental results show that the system can effectively distinguish three typical emotional states: excitement, anxiety and relaxation, with a classification accuracy of 78.5%. This study provides a wearable and low-cost solution for companion animal emotion monitoring and lays the foundation for future research on ubiquitous animal-computer interaction (ACI).

Ccs Concepts

• Human-centered computing → Ubiquitous and mobile computing systems and tools • Computing methodologies → Machine learning • Applied computing → Life and medical sciences

Keywords

Companion animal emotion monitoring, wearable computing, multimodal sensing, machine learning, ubiquitous computing, physiological signal processing, animal-computer interaction (ACI), canine health assessment

ACM Reference format:

Yibo Meng, Ziyuan Qu and Yan Guan. Companion Animal Emotion and Health Status Monitoring Based on Wearable Multimodal Sensing. 2025. In *Companion of the 2025 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp Companion'25), October 12–16, 2025, Espoo, Finland. ACM, New York, NY, USA*, 5 pages. https://doi.org/10.1145/3714394.3756321*ACM, October 12-16, 2025, Espoo, Finland.* https://doi.org/10.1145/3714394.3754404

1 Introduction

Companion animals, especially dogs, have been deeply integrated into modern human society and have become an indispensable member of millions of families. They not only provide companionship but also play an increasingly important role in human emotional support, mental health and even auxiliary treatment [1, 2]. The unique emotional bond (Human-Animal Bond, HAB) formed between humans and animals has a profound impact on the well-being of both parties [3, 4]. The quality of this bond is often related to humans' ability to understand and respond to the needs of pets. Therefore, promoting universal concern for animal welfare and the desire for deeper emotional connection has become a significant social trend.

However, the "communication gap" inherent in this cross-species intimate relationship - animals cannot directly express their complex internal emotional states and physiological needs through human language - constitutes a major obstacle to understanding and meeting their well-being. Humans' interpretation of pet emotions often relies on subjective observation and empirical inference, which is easily affected by individual bias, knowledge limitations and situational noise, leading to misunderstanding or even ignoring the true feelings of animals [5, 6]. For example, dogs may exhibit subtle behavioral changes when facing stress or discomfort, which can be easily overlooked by ordinary owners who are not familiar with their behavioral spectrum [7]. This misunderstanding may not only lead to inappropriate care and delay the identification of potential health problems (such as chronic pain or anxiety) but may also cause behavioral problems in pets and even weaken the emotional connection between humans and pets, negatively affecting the quality of life of both parties [8]. Therefore, how to effectively bridge this communication gap and enable humans to understand their companion animals more accurately and empathetically has become an emerging and important research topic in the field of human-computer interaction (HCI), especially in the subfield of animal-computer interaction (ACI) [9, 10]. One of the goals of ACI is to explore how technology can support and enhance human understanding and care for animals [11].

Advances in ubiquitous computing and wearable sensing technology provide us with unprecedented opportunities to continuously and objectively capture physiological and behavioral data streams reflecting the status of animals through non-invasive or minimally invasive technologies [12, 13]. These data, such as electrodermal activity (EDA/GSR), heart rate (HR) and heart rate variability (HRV), and activity patterns, are considered biomarkers associated with emotional arousal, stress levels, and overall health [14, 15]. Recent studies have demonstrated the potential of using wearable sensors for fine-grained identification of canine activities and behavioral context analysis [16, 17], and have even begun to explore technical approaches to enhance human-canine emotional

This work is licensed under Creative Commons Attribution International 4.0.

UbiComp Companion '25, Espoo, Finland

© 2025 Copyright is held by the owner/author(s).

ACM ISBN 979-8-4007-1477-1/2025/10.
https://doi.org/10.1145/3714394.3754404

connection based on biometric feedback [18]. Researchers in the field of ACI are actively exploring how to design and deploy these technologies not only as data collection tools, but also as a medium that can enhance human understanding of animals, promote positive interactions, and ultimately improve animal welfare [10, 19]. Although existing work has made progress in using technology to monitor animal behavior and physiology [13, 17], challenges remain in the following aspects, especially from the perspective of HCI and ACI:

1. Multimodal data fusion and deepening of contextual understanding: Emotions are complex and difficult to fully capture with a single sensor modality. Although some studies have begun to integrate multiple sensors [20], in the field of companion animals, how to effectively integrate data from different physiological and behavioral sensors and interpret them in specific human-pet interaction situations [21] to provide a more holistic and detailed portrait of the animal's status is still an issue that needs to be explored in depth.

2. Transformation of data into insights and presentation to nonprofessional users: Even if rich physiological data is collected, how to transform it into "insights" that non-professional users such as pet owners can easily understand and take positive actions based on it is a core challenge in HCI design [22]. Simple raw data displays are often insufficient to support effective decision-making and interaction adjustments and require carefully designed abstractions and visualizations.

3. Animal-centric design, long-term usability, and maintenance of natural behavior: The design of wearable devices must prioritize the comfort and safety of animals and minimize interference with their natural behavior [9, 23]. At the same time, the long-term usability of the system, the stability of data collection, and the robustness in real home environments are key HCI considerations and are also areas that current research needs to continue to focus on [13, 16].

4. Promote positive human-pet interaction and empathy: Beyond simple status monitoring, HCI/ACI systems should explore how to use the information obtained to guide and promote healthier and more positive human-pet interaction patterns [18] and even enhance human empathy for animal companions [24].

Based on the above background, this study aims to design, develop, and evaluate a multimodal wearable system that integrates electrodermal activity (EDA/GSR), photoplethysmography (PPG) to obtain heart rate (HR) and heart rate variability (HRV), and inertial measurement unit (IMU) to non-invasively monitor physiological and behavioral indicators of companion dogs. Our core goal is not only to collect and analyze data at the technical level, but also to explore how the system can serve as a medium to enhance human-pet understanding and interaction. Specifically, we focus on how to transform complex physiological signals into emotional state clues (such as relaxation, positive anticipation, mild anxiety, play, etc.) that are more interpretable to owners by fusing multimodal data and applying advanced signal processing techniques (such as using NeuroKit2 [25]), and preliminarily explore how this information potentially affects owners' perception, decision-making, and interaction behaviors with their pets. This study hopes to provide design ideas, technical solutions, and empirical support for the development of ubiquitous computing systems that can promote deeper emotional connections between humans and pets and improve animal welfare through experimental verification in a semi-natural home environment.

2 Systemdesign

The design of this system adheres to the principle of user centeredness (considering both animal users and human users), aiming to create a system that can effectively and comfortably collect physiological and behavioral data of companion dogs, and transform these data into information that can be understood and used by owners, in order to promote more positive human-pet interactions and improve animal welfare. The system's design iterations refer to the methodology of Animal-Centered Design [9, 26].

2.1 Animal-Centric Wearable Node Design The design of the wearable sensor node puts the comfort, safety and natural behavior of the animal first, and strives to minimize the physical and psychological burden on the animal [18, 23].

● Microcontroller (MCU) and core components: Seed Studio Xiao BLE Sense (nRF52840) is selected as the main control unit. Its small size (20mm x 17.5mm), low power consumption (supports deep sleep mode), integrated BLE 5.0 and onboard IMU make it an ideal choice for wearable applications, helping to achieve the design goals of miniaturization and lightweight.

●Physiological signal sensor and wearing considerations:

○ Skin electrode activity (EDA/GSR) sensor (Grove GSR): Considering the challenges of canine skin and hair characteristics to signal quality [12], we designed a solution using flexible conductive fabric electrodes (e.g., silver fiber fabric) and explored fixing them on the dog's flank or chest where the hair is relatively sparse and the activity interference is small. The electrodes are fixed with a breathable, elastic custom strap, which is adjusted by Velcro or buckles to ensure stable contact and comfortable wearing.

● Photoplethysmography (PPG) sensor (MAX30102): The challenge with PPG sensors is their high sensitivity to stable skin contact and avoiding motion artifacts [4]. We prioritize integration into ear clip attachments (for use on the inner side of the pinna, where hair is thin and skin is low) or affixed to areas of thin skin, sparse hair, and high blood flow (e.g., near the groin, using either medical-grade hypoallergenic biocompatible adhesive or custom tight-fitting fixtures). The design process will evaluate the impact of different fixation methods on signal quality and animal acceptance through iterative prototypes and animal trials.

● Behavioral sensors:

○ Inertial measurement unit (IMU - onboard LSM6DS3): Used to capture the dog's macroscopic activity level, posture changes, and identifiable behavioral patterns such as running, jumping, resting, and shaking [5, 16]. The IMU module is in the body of the device and fixed to the center of the dog's back (between the shoulder blades) via a harness, which is a good location for monitoring overall trunk motion and minimizing movement restrictions.

● Physical form and materials: The device shell is made of lightweight, biocompatible 3D printing materials (such as medical-grade resin or flexible TPU), and the edges are rounded to avoid physical damage or discomfort to animals. The overall design pursues miniaturization and streamlining, and the target weight is controlled within 30 grams to meet the wearing requirements of small dogs. The fixed strap uses soft, breathable, easy-to-clean and elastic fabric materials to ensure stability and comfort of wearing and avoid friction and compression.

● Power supply and battery life: A small lithium polymer battery (such as 3.7V, 200-350mAh) is used, and a low-power management strategy is integrated (such as dynamically adjusting the sampling rate according to the activity status, intermittent BLE broadcasting). The target battery life covers a typical daily activity cycle or a complete experimental observation session (such as 2-4 hours) and considers the convenience of charging (such as a magnetic charging interface).

2.2 Data Acquisition and Wireless Transmission The firmware (written based on Arduino and nRF5 SDK features) is responsible for reading data from each sensor at a preset frequency (e.g., EDA 10-20Hz, PPG raw signal 50-100Hz, IMU 25-50Hz) with a high-precision device timestamp (millisecond level). The data is sent to the central device via BLE as a notification. We focus on the format design of the data packet to balance information integrity and transmission efficiency and consider using data compression or summary transmission strategies when the data volume is large to reduce the energy consumption of wireless transmission. The reliability of data transmission is guaranteed to a certain extent by the retransmission mechanism of the BLE protocol stack, and the data packet sequence number is recorded at the application layer to detect loss.

2.3 Human User Data Interaction and Interpretation Interface (Design Considerations) Although the focus of this paper is on system design and data analysis methods, a complete HCI system must consider how data is presented to human users to support their understanding and actions. Therefore, at the system design level, we pre-considered the following principles of interactive interface design, and the design and evaluation of this part is the focus of future work:

● Data visualization and abstraction: Raw physiological data is difficult for ordinary pet owners to interpret directly [17, 22]. The final output of the system should transform complex signal processing results (such as SCL, SCR features, HRV indicators obtained by NeuroKit2 analysis) into a more intuitive and easier to understand form, such as:

○Emotional state indicator: Based on the analysis model, concise visual elements (such as color-coded dashboards, dynamic icons, and summary emotional words) are used to roughly indicate the pet's current possible emotional state (e.g., "calm and relaxed", "active and excited", "slightly nervous").

● Trend charts and interpretations: Display the changing trends of key physiological indicators (such as average arousal level, HRV relaxation index, and activity energy consumption) over time (hours, days, weeks), supplemented by brief text interpretations to help owners understand the dynamics and potential patterns of their pets' status.

● Activity and behavior summaries: Provide daily or hourly activity statistics and identified major behavioral patterns (such as sleep duration, play duration, and number of barking times).

● Generative AI-Powered Interaction and Interpretation Layer: To truly bridge the gap between complex data and user understanding, we propose leveraging a Large Language Model (LLM) to transform the system from a data logger into an intelligent interpretive companion. This layer introduces novel interaction paradigms:

● From Data to Dialogue: The system can generate rich, natural language summaries that contextualize physiological data. Instead of just a label, an owner might receive a "daily diary" from the pet's perspective: "I was a bit anxious this afternoon when that loud thunder happened (your system noted a sharp rise in my EDA), but I felt much better after you came over to pet me." This transforms raw data into an empathetic narrative.

● Conversational Interface: Owners can query their pet's status using natural language, such as asking, "How was Sparky while I was at work today?" The LLM would synthesize sensor data and contextual information to provide a comprehensive summary, creating a dialogue-based interaction with the system.

● Contextualized information and personalized suggestions: Combine physiological data with contextual information that the owner may provide (such as "just came back from a walk", "there are guests at home", "home alone") to provide more targeted interpretations and personalized interaction suggestions [cf. 18]. For example, if the system detects that the pet's physiological arousal level is continuously high when alone, it may prompt the owner to pay attention to separation anxiety issues and provide some relief suggestions or guide them to consult professionals.

● Interactive exploration and empowerment of owners: Allowing owners to mark specific events or behaviors (such as "thunder" and "training") and view changes in the pet's physiological data before and after the event, helping owners to establish a connection between behavior and physiological response, improving their observation and understanding abilities, and empowering them to become more competent caregivers [24]. The system can also design a feedback mechanism to encourage owners to take positive interactive behaviors and observe the immediate impact of these behaviors on the pet's condition.

2.4 Offline Data Processing and Analysis Pipeline

The collected data will be processed offline in the Python environment. The core is:

1. Data loading, cleaning and behavior data synchronization: Use tools such as Pandas and use tools such as BORIS [27] or ELAN to assist in the accurate annotation and timestamp export of behavior videos.
2. Advanced physiological signal processing: Focus on using NeuroKit2 [25] to professionally process EDA and PPG signals, extract SCL/SCR features and HRV indicators [10, 14].
3. Activity feature extraction: Calculate the activity amount and its statistical features from IMU data and possibly explore simple behavior classification based on machine learning.

Feature engineering, statistical analysis and machine learning: Construct feature sets, use statistical methods such as mixed effect models [28] to analyze the differences in features under different emotional states, and use machine learning models [29] to evaluate the performance of predicting emotional states based on multimodal features.

The analysis results will be used to iteratively optimize the effectiveness of information presentation strategies and interaction suggestions for future user interfaces. Through such system design, we not only focus on data collection and analysis at the technical level, but also emphasize how to use technology as a bridge to enhance understanding, empathy and positive interaction between people and pets, which is the core concern of the HCI and ACI fields, aiming to ultimately improve the mutual well-being of both parties [9, 19].

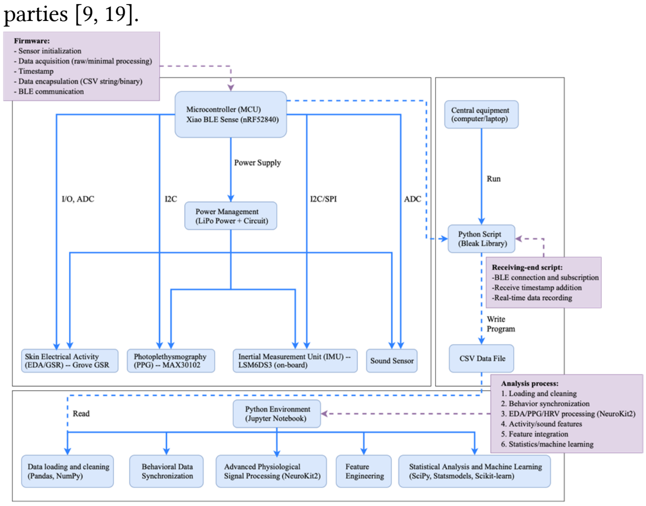

Figure 1: System structure diagram

3 Evaluations

3.1. Evaluation Purpose

Verify the effectiveness of this system in identifying three typical emotional states (excitement, anxiety, relaxation) of dogs through multimodal physiological and behavioral data, evaluate classification accuracy and contribution of key features.

3.2. Experiment Design

3.2.1 Experiment Subject We recruited 10 healthy adult dogs (5 females and 5 males, weighing 5-15KG, of the Golden Retriever breed) and 10 of their owners; Two professional dog trainers were recruited to assess the emotions of adult dogs.

3.2.2 Experiment Procedure Using different forms to induce emotional reactions in experimental dogs. Compare the emotional results evaluated by our designed system with those evaluated by the dog trainer and the pet owner. Each emotional state is induced through a standardized paradigm, lasting for 5 minutes each time with a 30- minute recovery period. Specifically, as shown below:

	Introduction Method	Expected Physiological Response
Excitement	Toy interaction (fetching ball), owner calling	Increased excitement (Elevated EDA, Increased HR, High activity level)
Anxiety	Isolation in unfamiliar environment, sudden loud noise (100dB 0.5s)	Increased anxiety (More SCRs, Decreased HRV, Trembling behavior)
Relaxation	Gentle petting in quiet environment, soothing music	Relaxation (Stable SCL, Decreased HR, Low activity level)

Figure 2: Experimental design to predict pet emotions in different states

3.2.3 Ethical Verification This experiment has been approved for ethical evaluation by Shanghai University of Technology. All participants are aware of all experimental procedures. All data is strictly anonymized and destroyed after data analysis.

3.3 Result

Analysis	System Accuracy[%]	Owner Feedback Accuracy[%]	Professional Trainer Feedback Accuracy (%)
Relaxation	74.3	55.4	75.7
Excitement	79.5	96.5	81.9
Anxiety	67.6	45.7	72.4

Figure 3: Preliminary verification results of the system prediction accuracy

4 Discussion

The experimental results indicate that the system performs well in predicting pet emotional perception, especially in the perception of relaxation and anxiety, which is significantly stronger than the perception of pet owners.

5 Conclusion

This experiment verified the effectiveness of the multimodal wearable system in recognizing canine emotions, and the accuracy of the system's emotion perception was significantly better than traditional observation methods. In the future, performance can be further improved by increasing sensor fusion dimensions (such as body temperature) and optimizing motion artifact elimination algorithms.

Acknowledgments

This study was supported by Tsinghua University and University of Shanghai for Science and Technology. We would like to thank every pet and owner who participated in this study.

References

[1] WALSH, F. (2009). Human-Animal Bonds I: The Relational Significance of Companion Animals. Family Process, 48(4), 462 - 480. https://doi.org/10.1111/j.1545-5300.2009.01296.x

[2] Fine, A. H. (2010). Handbook on animal-assisted therapy. Theoretical foundations and guidelines for practice. In Academic Press eBooks. Academic Press. https://doi.org/10.5167/uzh-46614

[3] Serpell, J. A., & Paul, E. S. (2011). Pets in the Family: An Evolutionary Perspective. In Oxford Handbooks Online. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780195396690.013.0017

[4] The American Pet Products Association (APPA) Releases 2024 Dog and Cat Owner Insight Report. (2024). Americanpetproducts.org. https://doi.org/109993644/1724699323838

[5] Bennett, P. C., & Rohlf, V. I. (2007). Owner-companion Dog interactions: Relationships between Demographic variables, Potentially Problematic behaviours, Training Engagement and Shared Activities. Applied Animal Behaviour Science, 102(1-2), 65-84. https://doi.org/10.1016/j.applanim.2006.03.009

[6] Mills, D. S. (2005). What' s in a word? A review of the attributes of a command affecting the performance of pet dogs. Anthrozoös, 18(3), 208 - 221. https://doi.org/10.2752/089279305785594108

[7] Casey, R. A., Loftus, B., Bolster, C., Richards, G. J., & Blackwell, E. J. (2014). Human directed aggression in domestic dogs (Canis familiaris): Occurrence in different contexts and risk factors. Applied Animal Behaviour Science, 152(152), 52-63. https://doi.org/10.1016/j.applanim.2013.12.003

[8] Mancini, C. (2011). Animal-computer interaction. Interactions, 18(4), 69 - 73. https://doi.org/10.1145/1978822.1978836

[9] Mancini, C., Lawson, S., & Juhlin, O. (2017). Animal-Computer Interaction: The emergence of a discipline. International Journal of Human-Computer Studies, 98, 129-134. https://doi.org/10.1016/j.ijhcs.2016.10.003

[10] Mancini, C. (2017). Towards an animal-centred ethics for Animal - Computer Interaction. International Journal of Human-Computer Studies, 98, 221 - 233. https://doi.org/10.1016/j.ijhcs.2016.04.008

[11] Jukan, A., Masip-Bruin, X., & Amla, N. (2017). Smart Computing and Sensing Technologies for Animal Welfare. ACM Computing Surveys, 50(1), 1 - 27. https://doi.org/10.1145/3041960

[12] Wang, X., Yu, H., Kold, S., Rahbek, O., & Bai, S. (2023). Wearable sensors for activity monitoring and motion control: A review. Biomimetic Intelligence and Robotics, 3(1), 100089. https://doi.org/10.1016/j.birob.2023.100089

[13] Whitham, J., & Miller, L. (2016). Using technology to monitor and improve zoo animal welfare. Animal Welfare, 25(4), 395 - 409. https://doi.org/10.7120/09627286.25.4.395

[14] Kreibig, S. D. (2010). Autonomic nervous system activity in emotion: A review. Biological Psychology, 84(3), 394 - 421. https://doi.org/10.1016/j.biopsycho.2010.03.010

[15] Shaffer, F., & Ginsberg, J. P. (2017). An Overview of Heart Rate Variability Metrics and Norms. Frontiers in Public Health, 5(258). https://doi.org/10.3389/fpubh.2017.00258

[16] Anniek Eerdekens, Arne Callaert, Deruyck, M., Martens, L., & Joseph, W. (2022). Dog ' s Behaviour Classification Based on Wearable Sensor Accelerometer Data. Ghent University Academic Bibliography (Ghent University). https://doi.org/10.1109/ciot53061.2022.9766553

[17] Alavala, N., Chen, H., Singhal, R., & Dhekne, A. (2022). PetTrack. Proceedings of the 2022 Workshop on Body-Centric Computing Systems. https://doi.org/10.1145/3539489.3539587

[18] Kleinberger, R., Ashooh, L., Farsad, K., & Hirskyj-Douglas, I. (2025). Animals' Entanglement with Technology: a Scoping Review. Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems, 1 - 22. https://doi.org/10.1145/3706598.3713384

[19] Ritvo, S. E., & Allison, R. S. (2017). Designing for the exceptional user: Nonhuman animal-computer interaction (ACI). Computers in Human Behavior, 70, 222-233. https://doi.org/10.1016/j.chb.2016.12.062

[20] Qiu, S., Zhao, H., Jiang, N., Wang, Z., Liu, L., An, Y., Zhao, H., Miao, X., Liu, R., & Fortino, G. (2022). Multi-sensor information fusion based on machine learning for real applications in human activity recognition: State-of-the-art and research challenges. Information Fusion, 80, 241-265. https://doi.org/10.1016/j.inffus.2021.11.006

[21] Maxwell, M. E., Kapla, S., Bright, T., & Echterling-Savage, K. (2021). Companion Animal Behavior Analysis. Applications of Behavior Analysis in Healthcare and Beyond, 415-429. https://doi.org/10.1007/978-3-030-57969-2_19

[22] Lakmal Meegahapola, Constantinides, M., Zoran Radivojevic, Li, H., Quercia, D., & Eggleston, M. S. (2023). Quantified Canine: Inferring Dog Personality From Wearables. ArXiv (Cornell University), 1-19. https://doi.org/10.1145/3544548.3581088

[23] Byrne, C., Zuerndorfer, J., Freil, L., Han, 1-20. https://doi.org/10.1145/3161184

[24] Pons, P., & Jaen, J. (2017). Designing interspecies playful interactions. Proceedings of the Fourth International Conference on Animal-Computer Interaction. https://doi.org/10.1145/3152130.3152139

[25] Makowski, D., Pham, T., Lau, Z. J., Brammer, J. C., Lespinasse, F., Pham, H., Schölzel, C., & Chen, S. H. A. (2021). NeuroKit2: A Python toolbox for neurophysiological signal processing. Behavior Research Methods. https://doi.org/10.3758/s13428-020-01516-y

[26] Mancini, C. (2023). Responsible ACI: Expanding the Influence of Animal-Computer Interaction. Open Research Online (the Open University), 1 - 9. https://doi.org/10.1145/3637882.3637895