Literature Survey Of CNN-Dog Emotion Classification

By

Annisha S

Gokila N

Indujha N

Jayalakshmi S

Keerthana R

Mathubala S

1) Understanding Dog Emotions Through Deep Learning: A CNN-based Classification Framework

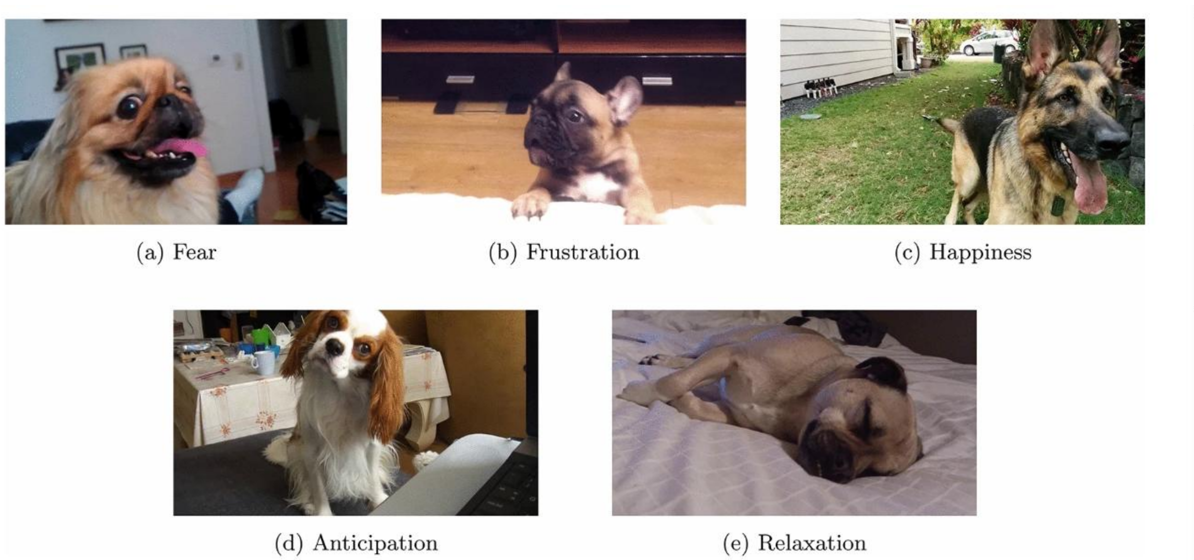
https://ieeexplore.ieee.org/abstract/document/10722523

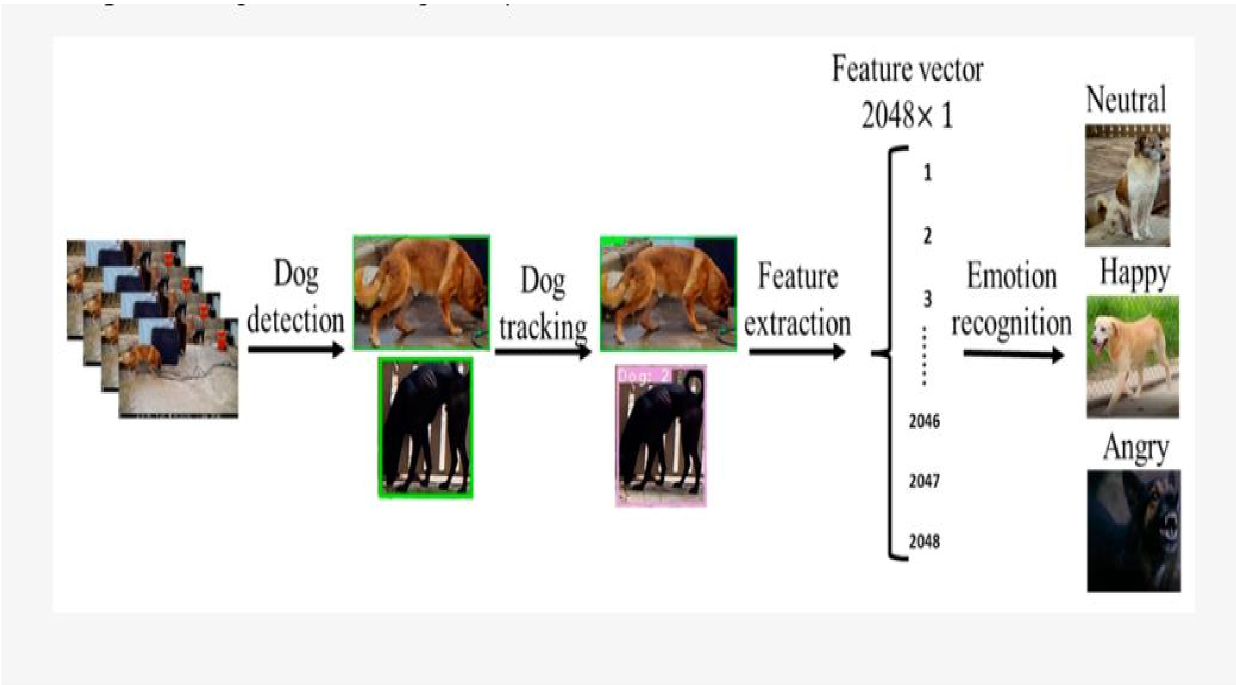
Introduction

Emotions in animals, particularly dogs, play a vital role in welfare monitoring and human–dog interaction. Traditional methods for assessing canine emotions rely on behavioral observation, which is often subjective and inconsistent. Recent advances in computer vision and deep learning provide opportunities to automate this process. The paper *Understanding Dog Emotions Through* Deep Learning: *A CNN-based Classification Framework* introduces a convolutional neural network (CNN) model to classify dog emotions from visual data.

Methodology

The authors designed a CNN-based framework capable of recognizing four emotional states: happiness, sadness, relaxation, and anger. A dataset of annotated dog face images was used for training and testing. Standard preprocessing and augmentation techniques were applied to improve robustness. The CNN model's performance was compared with classical machine learning methods such as Support Vector Machines (SVM) and K-Nearest Neighbors (KNN).





Results

The proposed CNN achieved significantly higher accuracy than baseline models, with reported performance exceeding 90% in public summaries. This demonstrates the effectiveness of deep learning in capturing subtle facial features and expressions that traditional approaches often miss. The results suggest that CNNs can provide reliable emotion classification in dogs when trained on properly labeled datasets.

Strengths and Limitations

The main strength of the framework is its ability to outperform traditional classifiers, highlighting the advantage of end-to-end feature learning. However, limitations include the relatively small dataset, the subjectivity of emotion labeling, and restricted generalization across breeds, lighting conditions, and contexts. Additionally, reliance on still images overlooks temporal and auditory cues, which are crucial in canine emotional expression.

Future Directions

Future research should focus on:

- Expanding datasets across diverse breeds and environments.
- Integrating multimodal cues such as vocalizations, posture, and video sequences.
- Employing explainable AI methods to make predictions interpretable to veterinarians and trainers.
- Conducting cross-dataset evaluations to ensure robustness and generalization.

Conclusion

This work demonstrates the promise of CNNs in recognizing canine emotions and marks a step toward practical applications in veterinary science and animal welfare. Nonetheless, for reliable real-world deployment, larger datasets, multimodal integration, and explainability must be prioritized.

2) Classification Of Dog Emotion Using Transfer Learning On Convolutional Neural Network Algorithm

http://jurnal.bsi.ac.id/index.php/paradigma/article/view/5295

Introduction

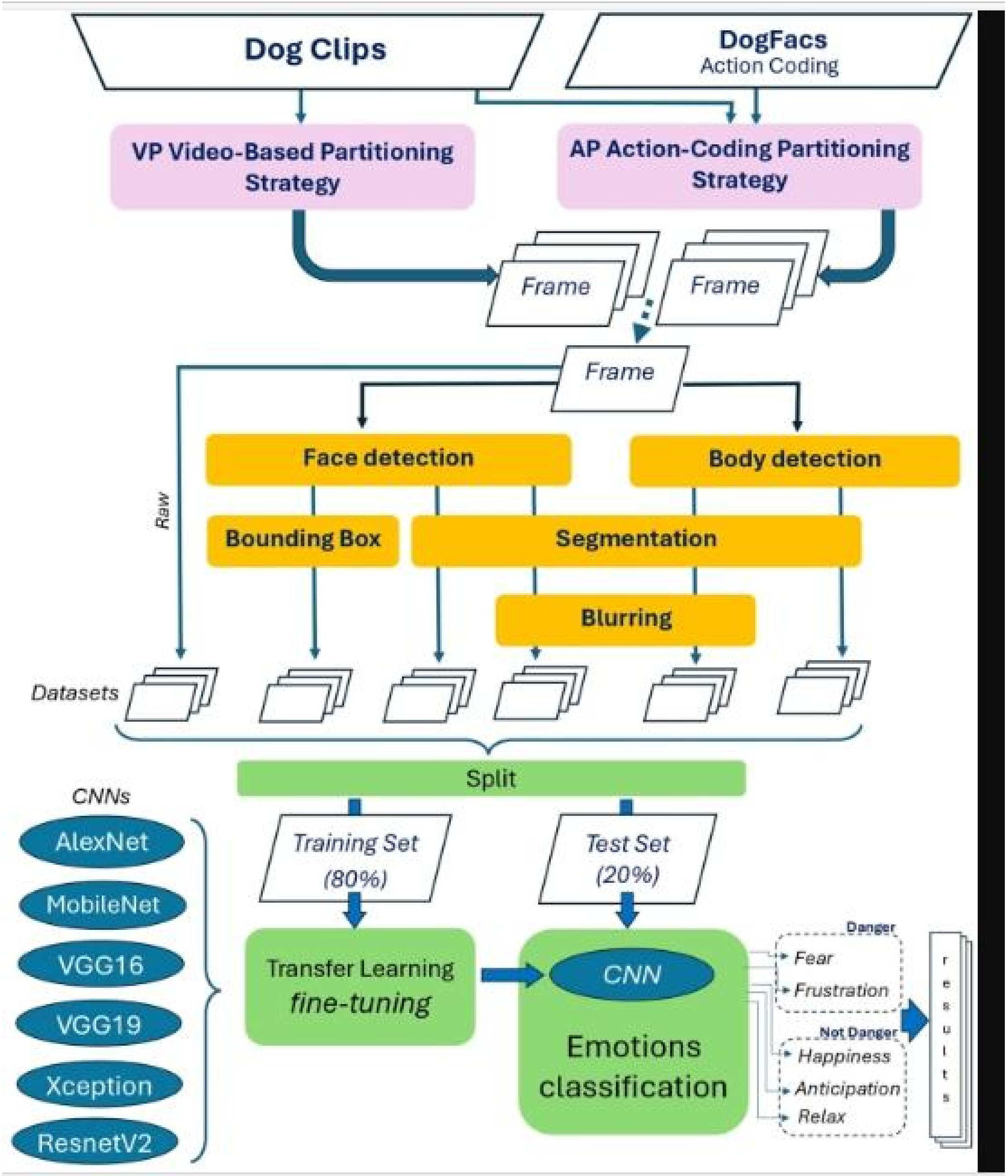
Understanding a dog's emotional state from its facial expressions is valuable for improving pet welfare, early detection of stress or disease, and enhancing the relationship between pets and their humans. Traditional image classification methods struggle when data are limited or emotions subtle. Transfer learning, which reuses features learned on large datasets (e.g. ImageNet), is a promising strategy to overcome these limitations.

Objective

The paper aims to classify dog emotions into four categories — anger, happiness, calmness, sadness — using images of dog facial expressions. The novelty is applying transfer learning (using VGG16) rather than training a CNN from scratch, to improve classification performance with limited data.

Methodology

- **Model architecture**: VGG16 (pretrained on ImageNet) is used for feature extraction. Transfer learning approach: freeze or fine-tune layers, then add classification layers (dense etc.). ResearchGate
- **Dataset & labels**: Facial images of dogs labelled into the four emotion classes. Preprocessing includes resizing, normalization; data split into training, validation, and test sets. ResearchGate
- **Training / evaluation metrics**: Accuracy on training, validation; F1-score on the test set. Possibly confusion matrix among emotion categories.



Results

- **Training accuracy**: ≈ **96.72%** ResearchGate
- **Validation accuracy**: ≈ **88.05%** ResearchGate
- **Test set**: average **F1-score** ≈ **84.30%** ResearchGate

These results suggest good performance, though lower metrics on validation/test vs training indicate some overfitting or domain gap.

Strengths

- Using transfer learning helps to get good feature representations even with limited data.
- Clear performance metrics (accuracy + F1-score) make evaluation fair.
- Four emotion classes is richer than just binary (positive/negative) classification.
- Practical relevance for pet welfare.

Limitations

- The gap between training accuracy (~96.7%) and test/validation (~84-88%) suggests possible overfitting or insufficient generalization.
- Labelling emotion from facial images is subjective; emotions in dogs may be better indicated by more than just facial expression (posture, context, body signals, vocalizations).
- Breed variation, lighting, angles etc. may affect real-world performance; not sure how varied the dataset is.
- F1-score averaged over test set may mask which classes are harder (e.g., calmness vs anger) — confusion between similar emotions may be high.

Future directions

- Expand dataset: more breeds, lighting conditions, angles, and contexts to improve generalization.
- Use other modalities: video (temporal cues), body posture, sound/vocalization, physiological signals to complement images.
- Use explainability methods (e.g. heat-maps, Grad-CAM) so one can see which facial regions contribute to prediction.
- Try other architectures (e.g. ResNet, EfficientNet, Vision Transformers) or ensemble methods to improve performance.
- Investigate class-wise detailed performance and error patterns to improve difficult cases.

Conclusion

This work demonstrates that *transfer learning with VGG16* is effective for multi-class dog emotion classification from facial images, achieving good accuracy and F1-score in test settings. While promising for applications in pet welfare and canine emotion recognition, further work is needed to improve generalization, include richer cues, and ensure robustness across real-world settings.

3) Reading emotions in dog eyes and faces by Japanese observers: A replication and extension study of Burza et al (2022)

https://www.sciencedirect.com/science/article/pii/S0376635725001081

Introduction

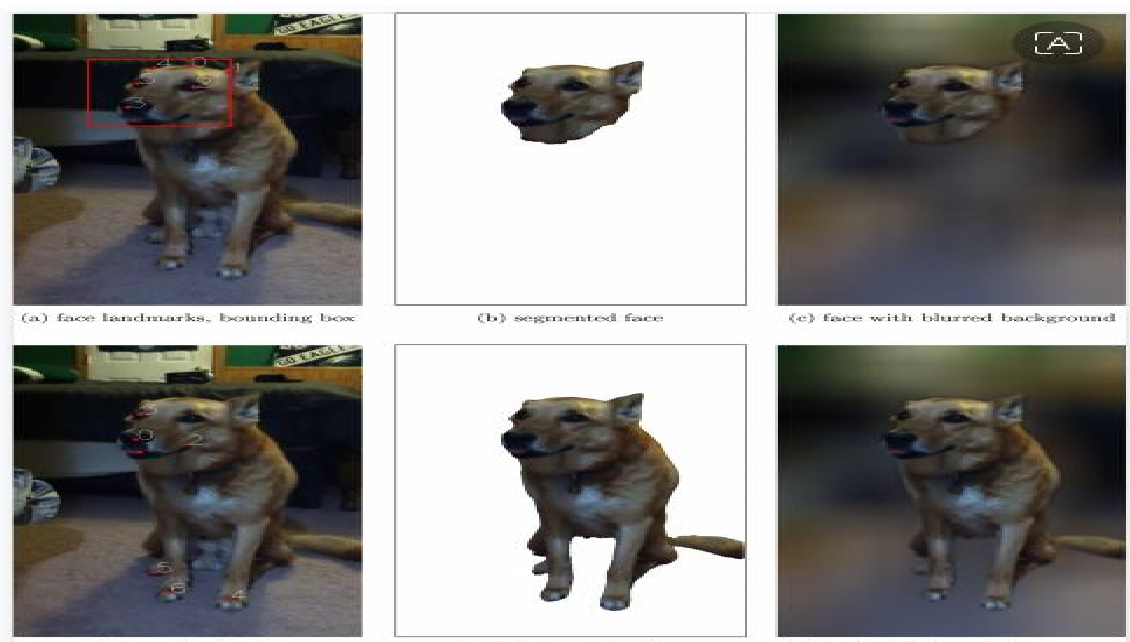
Human ability to infer emotions in dogs from facial expressions and eyes has been demonstrated in various Western and Brazilian populations. Burza et al. (2022) showed that people can identify basic emotions from either whole-faces or just eyes of dogs, better than chance. Your paper (Murata, Liu, Watanabe, 2025) seeks to replicate and extend those findings in a **Japanese** cultural context, exploring whether those effects generalize across cultures. ScienceDirect+1

Aim / Research Questions

- Can Japanese observers identify dog emotions (from whole-faces and eyes-only images) above chance level? ScienceDirect
- Does viewing full face vs eye-only affect accuracy? ScienceDirect
- Do factors such as dog ownership or participants' ability to recognize human emotions predict performance with dog emotion recognition? ScienceDirect
- Are there any cross-cultural differences in which dog emotions are more or less easily identified? ScienceDirect+1

Methodology

- Sample: 342 Japanese participants. ScienceDirect
- Stimuli: Photographs of dogs (three breeds) used previously in Burza et al. (2022). Stimuli included two types: full face, and eyes only. ScienceDirect
- Task: Participants viewed images and were asked to assign the dog's emotional state (forced choice among some set of emotion labels). ScienceDirect+1
- Additional measures: Participants' dog ownership status; human emotion recognition ability also assessed, to see if these predict dog-emotion recognition. ScienceDirect



Findings / Results

- Japanese participants were **significantly better than chance** at identifying dog emotions both from full face and eyes-only images. ScienceDirect
- Accuracy was *higher* when viewing **full face** images compared to eyes only — suggests contextual facial cues are important. ScienceDirect
- Dog ownership did **not** significantly affect accuracy. ScienceDirect
- Ability to recognize *human* emotions did **not** predict performance in recognizing dog emotions. Suggests different or partially independent processes. ScienceDirect
- Some **cross-cultural differences** emerged: in which specific emotions were most correctly identified compared to Burza et al.'s earlier results in other populations. ScienceDirect

Interpretation & Significance

- The study supports that the ability to read dog emotions from faces/eyes has some **universal components**: Japanese observers also succeed above chance, replicating Western/Brazilian results.
- The full-face advantage indicates that while eyes are informative, the rest of the face adds cues that help emotion inference.
- Lack of effect from dog ownership or human emotion recognition suggests that exposure or human emotion skill may not be major factors—or at least in this sample.
- Cross-cultural differences highlight perceptual or interpretative biases shaped by cultural experience or exposure to dogs of certain appearance/morphology.

Limitations

- Only three dog breeds used; morphological variation of dogs globally is much greater. Some breeds may express visibly different cues, possibly affecting recognition.
- Static images only; real emotion expression in dogs is dynamic and multimodal (posture, movement, sound) which are not captured.
- Forced choice emotion labels may constrain responses; real perception might involve subtler or mixed emotional states.
- Cultural sample is Japanese; more cultures would strengthen claims of universality vs specificity.

Future Directions

- Include more dog breeds, especially those with diverse morphological features (ear shape, coat, snout, etc.).
- Use dynamic stimuli (video), include vocalizations or context signals.
- Explore more varied cultural populations to map the influence of dog-related cultural exposure.
- Investigate neurological or perceptual basis: which facial features are driving judgments (eye whites, ear posture, mouth shape etc.), possibly via eye-tracking or feature analysis.

- Examine emotional categories in more detail to see which are reliably identified and which confuse observers.

Conclusion

This replication and extension study shows that Japanese observers can reliably infer dog emotions from facial cues, both from full faces and eyes alone, replicating prior findings in other cultures. The advantage of full-face images suggests that whole facial context matters. Cultural factors influence which emotions are more easily recognized, pointing to both universal and culture-specific components of cross-species emotion perception.

4) Automatic canine emotion recognition through multimodal approach

https://www.sciencedirect.com/science/article/pii/S0167865525002466

Introduction

Recognizing the emotional states of dogs automatically has many applications: welfare assessment, enhanced human-dog interaction, veterinary diagnostics, and more. Most prior work uses unimodal data (just images, or just physiological signals, etc.). This study introduces a **multimodal framework** that combines **visual**, **inertial**, and **physiological** data to improve emotion recognition accuracy in dogs. ScienceDirect

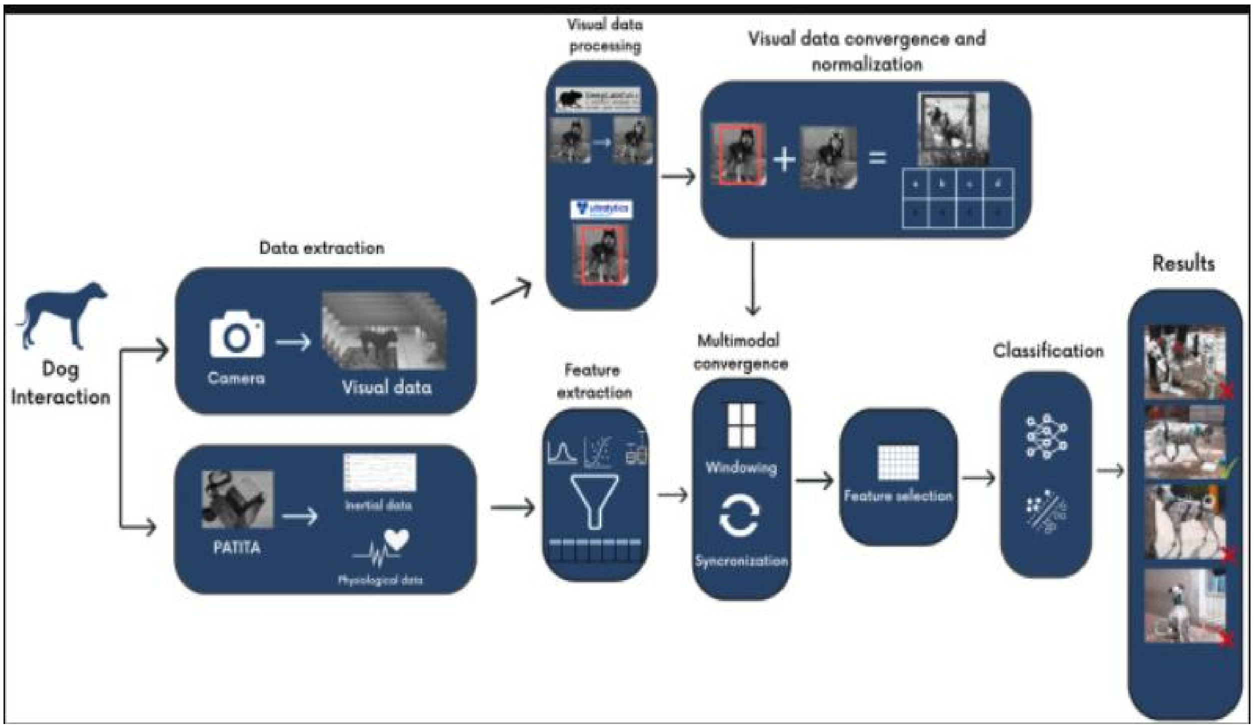
Objectives

- To collect multiple types of data from dogs—visual (images/video), motion/inertial sensors, physiological signals—and use them jointly to classify their emotional states. ScienceDirect
- To test whether multimodal information yields better recognition accuracy than single-modality approaches.
- To explore what features from each modality are most predictive and how they complement each other.

Methodology

- **Data collection**: Dogs are monitored with cameras (for their facial expression/body posture etc.), inertial sensors (for motion, orientation), and physiological devices (e.g. heart rate, skin conductance, etc.). The types of physiological data may include things like heart rate variability, though exact physiological measures used are to be confirmed. ScienceDirect
- **Emotion labels**: Emotions are mapped to discrete categories (e.g. "happy", "fearful", etc.). The labeling procedure may involve expert observation or standard behavioral indicators.

- **Model architecture**: Machine learning / deep learning model(s) that accept inputs from all modalities (probably separate modality-specific feature extractors + some fusion layer) to classify emotion. The study likely compares fusion strategies (early fusion, late fusion) and perhaps ablation (dropping one modality) to test contribution.



Results

- The multimodal approach **outperforms** unimodal models: combining visual + inertial + physiological data gives better classification accuracy than using any single source alone. ScienceDirect
- The study finds specific modalities contribute different predictive power; e.g. physiological data may help disambiguate emotions that look similar visually but differ in bodily arousal.
- Accuracy metrics (e.g. overall accuracy, maybe F1 scores) are improved when modalities are fused. Exact numbers were not visible in the search summary.

Strengths

- Use of **multimodal data** increases robustness—compensates where one modality is weak or ambiguous.
- More realistic in real-world settings: dogs' emotion expression is not just in face, but body movement, heart/physiology etc.
- The study pushes toward systems that could work live or in applied settings (shelters, clinical, etc.).

Limitations

- Collecting physiological/inertial data is more invasive or difficult than just video; may limit scalability or generalizability if equipment is not available.
- Synchronizing multiple data streams (visual, inertial, physiological) can be challenging; noisy data or missing data in some modalities can degrade performance.
- The emotion categories and ground-truth labels are tricky: what counts as “fear” or “happiness” can overlap, and labeling may rely on human judgments, which can have bias.
- Possibly limited sample size, dog breeds, contexts: if dataset is small or biased toward certain breeds or conditions (indoors, in lab), generalization may suffer.

Future Directions

- Larger and more diverse datasets: more breeds, age groups, different environments (indoors/outdoors), different lighting, etc.
- Better fusion methods: exploring which fusion strategy (early, late, weighted, attention-based) works best and is robust to missing modalities.
- Real-time emotion monitoring: develop systems that can process data streams live.
- Use explainable AI tools: help users understand what features (e.g. ears, tail posture, motion, physiological arousal) are driving classification.
- Multimodal including audio: dog vocalizations (barks, whines) often carry emotional content; including audio may further improve performance.

Conclusion

This paper demonstrates that combining visual, inertial, and physiological signals in a multimodal framework leads to more accurate canine emotion recognition than unimodal methods. It represents a significant step toward more naturalistic, robust, and applied systems for understanding dog affect. However, scaling up, refining labels and contexts, and ensuring usability in real settings remain necessary steps for future work.

5) Observational behaviors and emotions to assess welfare of dogs: A systematic review

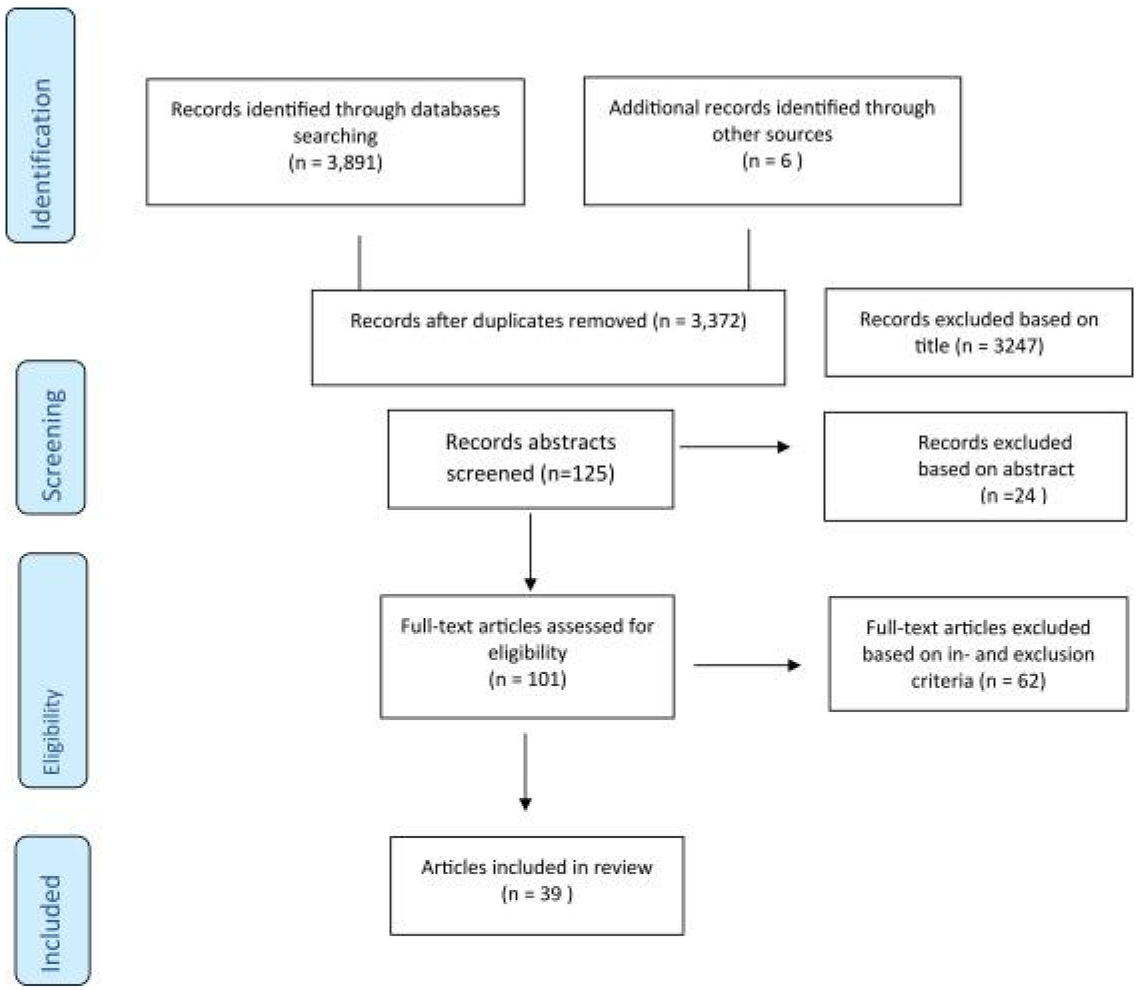
https://www.sciencedirect.com/science/article/pii/S1558787823001491

Introduction

Animal welfare science increasingly emphasizes not just physical health, but also emotional and behavioral indicators of well-being. In canine welfare, many studies use observational behavior to infer emotional states, but there is no unified framework or consensus about **which behaviors reliably indicate welfare**, how they are measured, or how valid these measures are. This systematic review by de Winkel et al. attempts to synthesize recent literature (past ~10 years) on observable behavior and emotion indicators in dogs to assess welfare. ScienceDirect+1

Methods

- The authors followed PRISMA guidelines for systematic reviews. University of Ghent Library
- They searched major databases (PubMed, ScienceDirect) between October & December 2021. University of Ghent Library
- Inclusion criteria: peer-reviewed articles in the last 10 years (from 2011-2021 approx.), dealing with **observable indicators** (behaviors) related to dog welfare and/or emotional state. University of Ghent Library
- Excluded: non-observable measures (e.g. internal states only), reviews, non-peer-reviewed works.
- Total included studies: **39**. University of Ghent Library



Findings / Key Themes

From the review, the authors identified **nine overarching themes** of behavioral indicators used across studies. Some of the most frequently reported were:

1. **Vocalizations** (e.g. whining, barking) as indicators of emotion or stress. University of Ghent Library
2. **Stress-related behaviors** (such as panting, lip-licking, paw lift, etc.). University of Ghent Library
3. **Interaction with the non-social environment**, e.g. exploratory behavior, avoidance, interest in surroundings. University of Ghent Library

Other themes included social interactions (with humans and with other dogs), posture and movement, facial expressions, play behavior, resting/relaxed behaviors, etc. University of Ghent Library

Most indicators were described in both positive and negative framing (i.e. some behaviors indicate good welfare, others poor welfare). University of Ghent Library

Strengths and Weaknesses in the Literature

- **Reliability and validity**: Only **5 out of 39** studies mentioned any form of validity assessment of their observational measures. University of Ghent Library
- **Inter-rater reliability**: More common — **23** studies reported some inter-rater reliability. University of Ghent Library
- There is *no standard set of behaviors* agreed upon across the field; substantial variation in what behaviors are used, how they're defined, how long observations last, contexts (shelter, home, clinic, assisted-interventions). University of Ghent Library

Implications / Significance

- This review helps map the landscape of how dog welfare is being assessed behaviourally. It shows that a variety of simple observational behaviors are frequently used, which is useful, since observations are relatively low-cost and non-invasive.
- Provides a basis to develop or refine standardized welfare assessment tools for dogs—especially in applied settings (shelters, clinical veterinary, animal-assisted interventions).
- Indicates strong need for more studies to validate the behavioral indicators (i.e. to show that certain behaviours really do map to emotional welfare states), and for greater consistency in measurement methods.

Limitations and Gaps Noted

- Many studies focus on negative welfare indicators (stress, fear) rather than positive welfare / positive emotional states (relaxation, contentment, play).
- Few instruments measure both behavior + physiological indicators in combined fashion; many rely purely on behavior.
- Heterogeneity across contexts, definitions, breeds, observer training etc., making cross-comparison difficult.
- Validity and reliability often under-reported; risk of bias in some observational measures.

Future Directions

- Develop and validate standard behavioral measures/instruments for welfare and emotion in dogs, including defining specific behaviors clearly, training observers, ensuring inter-rater reliability.
- Incorporate positive welfare indicators more; balance negative/positive emotional state observations.
- Use multimodal measures: combine behavior with physiological metrics (e.g. heart rate, cortisol) for more robust assessment.
- Longitudinal and real-life (ecological) settings rather than only controlled lab/shelter settings.
- Consider breed, age, individual temperament, environmental context when interpreting behaviors.

Conclusion

de Winkel et al.'s review pulls together recent work on observational behavioral indicators of welfare in dogs and shows that while there is a rich set of behaviors used across literature, there is not yet consensus or standardization in definitions, validity and measurement. The field would benefit from standardized, validated tools combining behavioral and physiological indicators, with attention both to positive as well as negative emotional states.

6) Towards a scientific definition of animal emotions: Integrating innate, appraisal, and network mechanisms

https://www.sciencedirect.com/science/article/pii/S0149763425001277

Introduction

Understanding animal emotions is important for fields like animal welfare science, behavior, ethics, and biology. However, definitions are often vague, relying on behavioral, physiological, or cognitive indicators without clear mechanisms. Carranza-Pinedo et al. propose a more rigorous, mechanistic framework by integrating three theoretical strands from human emotion research: **innate mechanisms**, **appraisal theories**, and **network theories**. The goal is to provide clearer hypotheses, better translation between human and animal emotion research, and more precise grounding for welfare assessments.

Contributions of the Paper

- **Integrated Framework** – The authors argue for combining these three theories to avoid limitations of each taken alone. Innate responses may overlook complexity; appraisal theories sometimes lack mechanistic detail; network theories sometimes are too abstract.

- **Clarity on Indicators vs Mechanisms** – It distinguishes between observable indicators (behaviors, physiological responses) and underlying mechanisms (what causes or processes lead to those indicators). Some indicators are *ambivalent* (occur in different emotional valences), others *undetermined* (could arise in emotional or non-emotional contexts).
- **Emotion vs Related Processes** – Discussion of how emotions relate to decision-making, mood, and other affective states. They compare *parallel architecture models* (emotions and decision processes are distinct but interacting) vs *unified models* (emotions are integral to goal-oriented decision processes).

Key Questions Addressed

The framework aims to help answer:

1. **Do animals experience emotions?** (by examining mechanistic criteria rather than only indicators)
2. **Which animals?** (Which taxa have sufficient nervous systems, behavioral complexity, and cognitive ability to satisfy parts of the framework)
3. **Which emotions?** (Which categorical or dimensional emotions could be reasonably attributed, given species' capacities)
4. **How similar/different from human emotions?** (In terms of mechanisms, structure, dynamics)

Strengths

- Provides a **clear theoretical basis** to move beyond loosely defined indicators.
- Helps unify research across disciplines (behavioral biology, neuroscience, welfare science).
- The framework is likely to encourage empirical studies that test mechanism, not just correlations.

Limitations & Challenges

- Empirical measurement of appraisal and network dynamics in non-human animals is difficult: interpreting subjective valuation in animals is a challenge.
- Innate vs appraisal boundaries may blur, especially in species with less documented cognitive complexity.
- Network models require rich data: longitudinal, multimodal, possibly neurophysiological measures that are often hard to obtain in many species.
- Ethical and practical constraints may limit what data can be gathered (invasive measurement, etc.).

Future Directions

- Empirical studies designed to test specific components of this framework (e.g. measuring appraisal responses, mapping network interactions) in various species.

- Development of metrics or proxies for appraisal in animals (e.g. through choice tasks, observable cognitive evaluation).
- Incorporation of comparative studies across taxa to see how mechanisms scale with brain structure, cognitive capacity.
- Applying this framework in welfare assessments: refining animal welfare tools to include mechanistic markers, not just external observations.

Conclusion

Carranza-Pinedo et al. make an important contribution by offering a structured, mechanistic definition of animal emotions combining innate, appraisal, and network theories. This helps advance clarity and rigor in emotion research in animals, offering a path to more testable hypotheses, better cross-species comparisons, and improved welfare assessment. However, realizing the full potential of this framework will require methodological innovation, richer data, and cautious interpretation.

7) The relationship between charitable giving and emotional facial expressions: Results from affective computing

https://www.sciencedirect.com/science/article/pii/S2405844023109364

Introduction

Understanding what motivates people to donate to charities is important for both fundraising effectiveness and ethical communication. Emotions are known to play a big role in prosocial behaviour. This study explores how people's emotional facial expressions (measured both by automatic affective computing software and by self-report) relate to the *amount* they donate when asked to donate to pet charities. It also compares the two methods of measuring emotion to see which may better predict donation behaviour. ScienceDirect

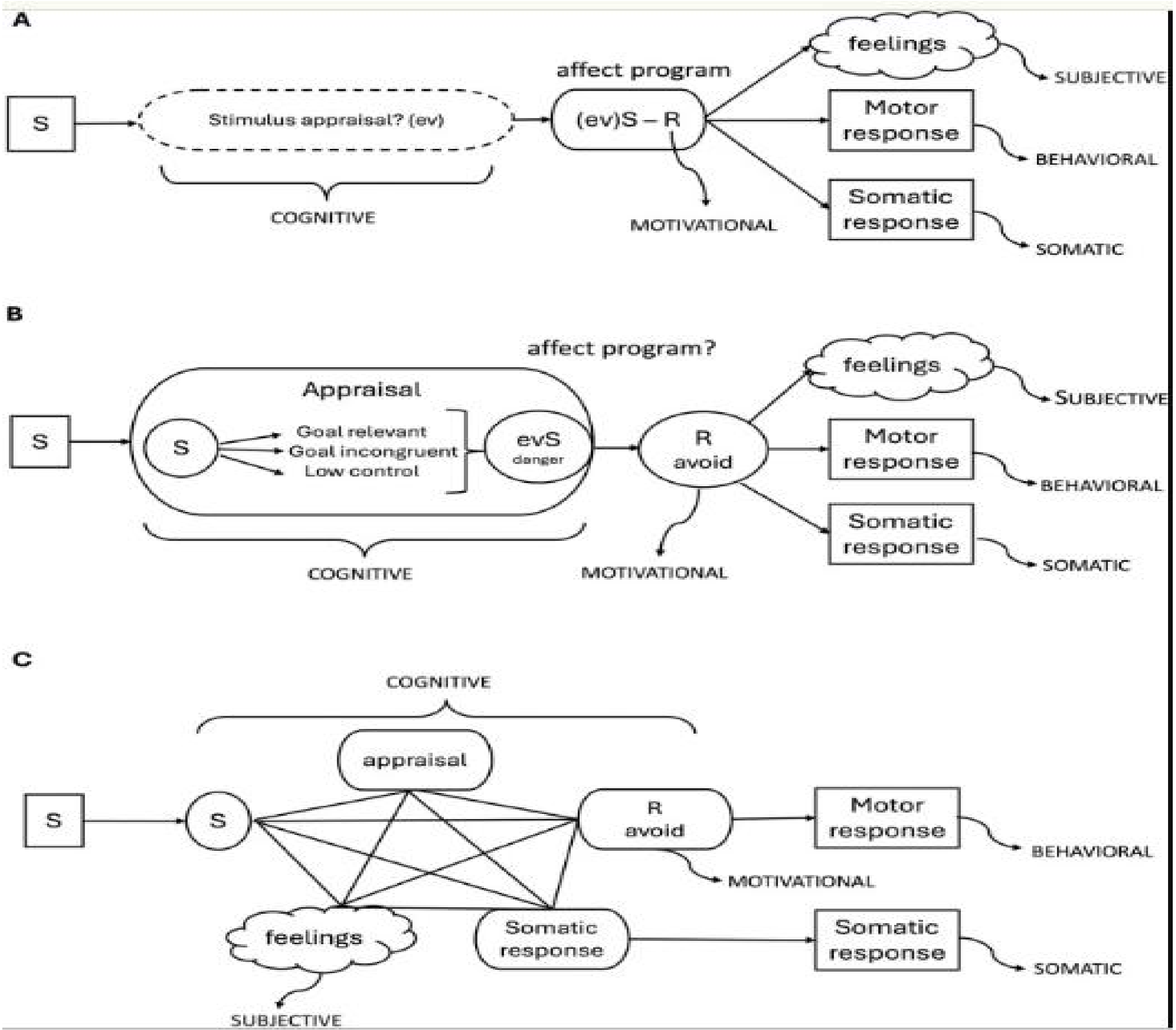
Objectives

- To examine relationships between basic emotional states (valence, arousal, and six "basic emotions": happiness, sadness, anger, fear, surprise, disgust) and **donation size** in the context of pet charities. ScienceDirect
- To compare **FaceReader** (automatic facial expression recognition) vs **self-report** emotion measurements in terms of how well they correlate with donation behaviour. ScienceDirect

Methodology

- **Participants**: 45 individuals were recruited for the study. ScienceDirect

- **Procedure**: Participants completed a donation task (donating to pet-charity appeals), while their facial expressions during the task were recorded and analysed; they also self-reported their emotional states. ScienceDirect
- **Measures**: Emotion metrics included valence, arousal, and the six basic emotions; donation size was the dependent variable. Emotion via FaceReader software for automatic detection; also via participants' self-reports. ScienceDirect



Key Findings

- **Sadness** and **anger** have a *positive* relationship with donation size (i.e. more sadness or anger → larger donations) ScienceDirect
- **Happiness** tends to relate *negatively* with donation size (more happiness → smaller donation) ScienceDirect
- **Arousal** (how emotionally activated or intense) was *not* significantly related to donation size. ScienceDirect

- Some basic emotions (surprise, fear, disgust) had inconclusive results in self-report data regarding association with donation size. ScienceDirect
- Similar patterns of effect from both FaceReader data and self-reports, though some differences in which effects are stronger. Using both methods improves prediction. ScienceDirect

Strengths

- Use of **multimethod measurement** (automatic and self-report) allows cross-validation and may capture unconscious/emotional cues that people don't self-report.
- Focus on *donation size* rather than just intention; this moves closer to measurable behaviour.
- Use of basic emotions plus valence/arousal gives more nuanced understanding of which emotions matter in giving.

Limitations

- Lab setting only; participants know they are in an experiment; might behave differently in real donation environments. ScienceDirect
- Small sample size (N = 45) limits generalizability.
- Limited to **pet charities**; results may differ for charities involving people, disasters, health, etc.
- Single-exposure to appeals; repeated exposure or long-term appeals might lead to different emotional responses.

Implications

- Unpleasant emotions (sadness, anger) may be more effective in fundraising appeals for pet charities (and perhaps more broadly) than positive emotions.
- Affective computing can act as a useful tool in predicting donation behaviour, possibly enabling fundraisers to test appeal materials in advance.
- Combining self-report and automated emotional measurement may improve the design and evaluation of charitable campaigns.

Future Directions

- Examine effects in different charity domains (human welfare, environmental, health) to see if patterns hold.
- Test in more ecological settings (real-life fundraising, online platforms) and with larger, more diverse participant pools.
- Explore repeated/trial exposure over time: do effects of sadness or anger diminish (or backfire) with overuse?
- Investigate more emotional dimensions (mixed emotions, dynamic facial expression over time) and other automatic detection tools.

Conclusion

This study provides evidence that emotions such as sadness and anger are positively related to how much people donate to pet charities, while happiness is negatively related, and arousal plays little role. It also shows that affective computing (FaceReader) complements self-reports and can help in predicting donation magnitude. These insights may help charities design more emotionally effective appeals, though caution is needed when generalizing beyond the experimental context.

8) Animal discomfort: A concept analysis using the domesticated pig (*Sus scrofa*) as a model

https://www.sciencedirect.com/science/article/pii/S1871141324001318

Introduction

In animal welfare research and legislation, the term **"discomfort"** is frequently used (in farming, biomedical studies, experiments, welfare laws, etc.), but its precise meaning is often vague or variable. Franchi et al. (2024) aim to clarify this by performing a **concept analysis** (using the Walker & Avant method) with the pig as a model species to develop an operational definition of animal discomfort. WUR+1

Methods

- **Literature search**: 2,594 documents in English from Scopus. WUR
- **Inclusion criteria**: Among those, 118 were retained because they either:
    1. Contained a definition and/or measurement of discomfort in animals including pigs, or
    2. Contained a definition or measurement of pain, suffering, or sickness in pigs only. WUR+1
- Concept analysis using Walker & Avant framework: identifying attributes, antecedents, consequences, defining empirical referents. ScienceDirect+1

Findings / Key Components

Through analysis of the 118 studies, the authors identified that "animal discomfort" broadly spans three intersecting domains:

1. **Physical discomfort** — e.g. injury, bodily pain, being too hot/cold, posture discomfort.
2. **Physiological discomfort** — e.g. stress responses, disease, internal disturbances (digestive, metabolic, fevers etc.).
3. **Mental discomfort** — negative affective states, uneasiness, psychological stress, anxiety. ScienceDirect+1

Other findings:

- Discomfort is induced by **internal or external stimuli**.
- It may be **short-lived or long-lasting**, and vary in severity (from mild to severe).
- It may **co-occur** with other negative affective states (pain, suffering).
- Behaviorally, animals show attempts to **avoid or alleviate** the source(s) of discomfort/unpleasantness. ScienceDirect+1

Operational Definition Proposed

Animal discomfort is a short- or long-lived negative affective state featured by physical, physiological and/or mental components, induced by internal or external stimuli, ranging from mild to severe, potentially occurring together with other negative affective states, and leading to avoidance or attempt to alleviate the source of uneasiness. ScienceDirect+1

Strengths

- Provides clarity: gives a shared definition that can help unify research, legislative language, welfare assessment.
- Use of systematic and rigorous method (Walker & Avant) to analyze how "discomfort" is used across many studies.
- Empirical basis: draws from many studies including pigs, making the definition grounded in observed usage/measurement.

- The inclusion of mental/psychological components, not just physical or physiological, helps capture more of what animals might feel.

Limitations / Challenges

- The concept analysis is based on literature; doesn't itself provide new empirical measurement tools.
- Mental discomfort / affective states are hard to measure directly in animals; relying on proxies, which may differ across species.
- The studies included may have variable quality, different definitions, measurement methods—introduces heterogeneity and possible bias.
- While pigs are a useful model, applicability to other species (especially non-mammals or species with different cognitive capacities) may be limited.

Implications & Future Directions

- Use in legislation and welfare standards: having a clear definition may help in drafting laws, guidelines, ethical permits.
- Empirical work: developing reliable, validated indicators (behavioral, physiological, perhaps cognitive) to operationalize "discomfort" per this definition.
- Cross-species research: see how this definition works for other domesticated species, wildlife, etc.
- Tools for assessment: welfare audits, guidelines for farm/husbandry conditions, experimental protocols could adopt this more precise definition to improve consistency.
- Investigation into thresholds: how mild vs severe discomfort differ, how internal vs external stimuli differ in their effects, etc.

Conclusion

Franchi et al. provide a useful conceptual clarification of "animal discomfort," particularly in pigs, which combines physical, physiological, and mental domains and emphasizes the negative affective state and behavioral avoidance/alleviation. This is a substantial foundation for more consistent research, policy, and welfare practice. For practical use, the next steps involve defining reliable indicators and ensuring cross-species and contextual relevance.