JOURNAL OF AGRICULTURAL DIGITALIZATION RESEARCH

# Bio-digital Integration and Cyber-physical Sensing Systems for Real-time Monitoring of Pollinator Health, Behavior, and Physiological Status: Advanced Technologies and Decision Support Frameworks for Sustainable Agricultural Ecosystems

**Elena G Vance [1*], Sarah J Kent [2]**
[1] Bio-Robotics Laboratory, Delft University of Technology, Netherlands
[2] Centre for Agri-Robotics and Automation, Queensland University of Technology, Australia

* Corresponding Author: **Elena G Vance**

## Article Info

**P-ISSN:** 3051-3421
**E-ISSN:** 3051-343X
**Volume:** 02
**Issue:** 01
**Received:** 06-12-2020
**Accepted:** 08-01-2021
**Published:** 10-02-2021
**Page No:** 09-15

**Abstract**
Pollinators provide critical ecosystem services valued at billions of dollars annually, yet populations face unprecedented decline due to habitat loss, pesticide exposure, pathogens, and climate change. Traditional monitoring approaches rely on manual surveys lacking temporal resolution and failing to capture dynamic physiological and behavioral responses to environmental stressors. Bio-digital integration—combining biosensors, wearable tracking devices, Internet of Things platforms, and artificial intelligence—offers transformative capabilities for real-time assessment of pollinator health at individual and colony levels. This review examines cyber-physical systems designed for pollinator monitoring, emphasizing miniaturized biosensors for physiological parameter measurement, radio-frequency identification and radar-based tracking technologies, edge computing architectures for distributed data processing, and machine learning algorithms for pattern recognition and anomaly detection. Applications span precision agriculture, where real-time pollinator activity data inform crop management decisions, and conservation biology, where early warning systems detect disease outbreaks and toxicological exposures. Despite technological advances, challenges persist in device miniaturization, energy autonomy, data interoperability, and ethical deployment. Future systems will require standardized protocols, multi-stakeholder engagement, and scalable architectures balancing ecological sensitivity with agricultural productivity.

**Keywords:** Bio-Digital Systems, Pollinator Health Monitoring, Cyber-Physical Agriculture, Biosensors, IoT Edge Computing, Precision Pollination

## 1. Introduction
### 1.1 Importance of Pollinators in Agro-ecosystems
Insect pollinators contribute to reproduction of over 75% of globally important crop species and 90% of wild flowering plants [1, 2]. The economic value of pollination services exceeds $577 billion annually across agriculture systems worldwide [3]. Managed honeybee colonies and wild pollinator communities—including bumblebees, solitary bees, butterflies, and hover flies—collectively determine reproductive success in crops ranging from almonds and apples to cucurbits and oilseeds [4, 5]. However, pollinator populations have experienced dramatic declines over recent decades. Honeybee colony losses average 30-40% annually in North America and Europe, while wild bee diversity has contracted by over 25% in agricultural landscapes [6, 7]. Causal factors include neonicotinoid and organophosphate pesticide exposure, parasitic mite infestations, viral and bacterial pathogens, nutritional stress from monoculture farming, and synergistic interactions among these stressors [8, 9].

### 1.2. Limitations of Traditional Pollinator Health Monitoring

Conventional pollinator monitoring employs manual techniques including visual colony inspections, pan trap surveys, transect counts, and laboratory bioassays [10]. These methods provide valuable population-level data but suffer from critical limitations. First, temporal resolution is inadequate—weekly or monthly sampling intervals fail to capture acute stress responses or sub-lethal effects of toxicological exposure [11]. Second, spatial coverage is restricted; labor-intensive surveys cannot scale across heterogeneous agricultural landscapes [12]. Third, observational approaches lack mechanistic insight into physiological processes underlying health deterioration, preventing early intervention [13]. Laboratory-based assessments offer mechanistic detail but disconnect organisms from ecologically relevant field conditions [14].

### 1.3. Scope and Objectives

This review examines bio-digital integration technologies enabling continuous, automated, and minimally invasive monitoring of pollinator health and behavior. We focus on cyber-physical systems combining biosensors for physiological measurement, digital tracking technologies for spatial behavior analysis, IoT architectures for distributed data acquisition, and artificial intelligence methods for pattern recognition. The objectives are to synthesize current capabilities in pollinator-specific sensing technologies, evaluate data integration frameworks supporting real-time health assessment, analyze applications in precision agriculture and ecosystem management, and identify technological and ethical challenges for field deployment.

## 2. Bio-digital Technologies for Pollinator Monitoring

### 2.1. Biosensors and Physiological Monitoring

Miniaturized biosensors enable direct measurement of physiological parameters indicative of pollinator health status (Table 1). Electrochemical sensors implanted in honeybee thoraxes monitor hemolymph glucose, lactate, and oxidative stress biomarkers with micromolar sensitivity [15]. These microelectrode arrays fabricated through MEMS techniques operate continuously for 48-72 hours before biofouling degrades signal quality [16]. Temperature microsensors embedded in bee abdomens track thermoregulation patterns, revealing colony-level fever responses to pathogen infection and individual hypothermia preceding pesticide-induced mortality [17]. Respiratory monitoring employs micro-respirometry chambers integrated into hive entrance tunnels, measuring $CO_2$ production and $O_2$ consumption as proxies for metabolic rate [18]. Optical sensors detect wingbeat frequency modulation—changes in flight motor patterns correlate with sublethal neurotoxic exposure [19]. Acoustic sensors capture buzzing frequency shifts indicative of Varroa mite parasitism and Nosema fungal infection [20]. Recent advances include flexible polymer substrates hosting multi-parameter sensor arrays attached to bee thoraxes via biocompatible adhesives [21]. Electroantennography sensors measure antennal electrophysiological responses to volatile organic compounds, assessing chemosensory function and detecting neurological impairment from pesticide exposure [22].

### 2.2. Digital Tracking and Localization Systems

Radio-frequency identification systems track individual pollinator movements with millimeter-scale spatial resolution (Table 3). Passive harmonic radar tags weighing 12-16 mg attach to bumblebee and honeybee thoraxes, enabling tracking over 100-900 meter ranges depending on transmitter power and antenna configuration [23, 24]. Active RFID tags with onboard batteries extend range to several kilometers but increase tag mass to 150-300 mg [25]. Automated optical tracking employs high-framerate cameras positioned at hive entrances, coupled with computer vision algorithms that identify individual bees via thorax patterns or attached visual markers [26]. Deep learning models achieve >95% accuracy in bee detection, trajectory reconstruction, and behavioral classification [27]. Radar-based tracking systems detect insect flight patterns across agricultural landscapes, differentiating bee species based on wingbeat modulation signatures and estimating pollinator flux into crop fields. Emerging technologies include miniaturized GPS units for large bee species and hybrid systems combining inertial measurement units with RFID for indoor/outdoor tracking continuity.

### 2.3. Integration with IoT and Edge Computing Platforms

Pollinator monitoring systems generate heterogeneous data streams requiring robust cyber-physical architectures (Figure 1). IoT platforms employ hierarchical sensing layers: sensor nodes attached to individual pollinators or distributed within hives; gateway devices aggregating data from multiple sensors; edge computing nodes performing local preprocessing; and cloud servers executing computationally intensive analytics. Communication protocols balance energy efficiency with data throughput. Bluetooth Low Energy enables 100-meter range transmission at <15 mA current draw, suitable for battery-powered wearable sensors. LoRaWAN supports multi-kilometer communication at ultra-low power, ideal for distributed environmental sensor networks in agricultural landscapes. Edge computing nodes execute lightweight machine learning models for real-time anomaly detection. Sensor fusion algorithms combine temperature, acoustic, and accelerometer data to classify behavioral states without cloud connectivity. Local preprocessing reduces bandwidth requirements by 80-95%, transmitting only summarized features or anomaly alerts to central servers.

## 3. Real-time Data Analytics and System Integration

### 3.1. Signal Processing and Data Fusion

Raw sensor data require preprocessing to extract biologically meaningful features while rejecting noise (Table 4). Temperature time series undergo Savitzky-Golay filtering to preserve circadian rhythm structure while removing high-frequency electronic noise. Wavelet transforms decompose acoustic signals into frequency-time representations, isolating queen piping events and worker bee communication patterns from ambient noise. Multi-modal data fusion integrates complementary information streams. Kalman filtering combines noisy GPS positions with IMU acceleration data to reconstruct smooth flight trajectories. Bayesian networks merge biosensor measurements with behavioral features to estimate integrated health scores. Feature extraction transforms raw sensor data into compact representations suitable for machine learning, including spectral analysis of wingbeat audio and kinematic parameters from video tracking.

### 3.2. AI-driven Health Assessment and Anomaly Detection

Machine learning algorithms enable automated health assessment from multi-parameter sensor data. Random forest classifiers trained on labeled datasets achieve 88-94% accuracy in disease detection from acoustic signatures, outperforming manual inspection. Support vector machines classify pesticide exposure levels from flight kinematics and foraging duration patterns with 85-91% sensitivity. Deep learning architectures process high-dimensional sensor streams. Convolutional neural networks analyze thermal imagery from hives, detecting abnormal temperature distributions indicative of queen loss or brood disease. Recurrent neural networks model temporal dependencies in time-series biosensor data, predicting colony collapse events 2-4 weeks before manual detection. Autoencoder architectures learn normal behavioral patterns, flagging statistical outliers representing stress responses. Transfer learning adapts models trained on laboratory data to field deployment contexts. Anomaly detection algorithms identify deviations from baseline patterns, with isolation forests detecting outlier sensor readings and change-point detection recognizing abrupt shifts in foraging activity preceding colony failure.

### 3.3. Cloud-Edge Architectures for Real-time Monitoring

Hybrid cloud-edge architectures optimize the trade-off between local responsiveness and centralized analytical power (Figure 2). Edge nodes execute lightweight inference models providing <500 millisecond latency for time-critical alerts, such as detecting acute pesticide exposure requiring immediate hive relocation. Cloud servers perform computationally intensive tasks including model retraining, population-level pattern analysis, and integration with external data sources. Real-time dashboards visualize pollinator health metrics for farm managers and researchers, displaying colony-level summaries alongside individual-level trajectories and physiological time series. Geospatial visualization layers overlay pollinator movement patterns on crop field maps, identifying under-pollinated zones and optimizing hive placement.

## 4. Applications in Agriculture and Ecosystem Management

### 4.1. Pollination Efficiency and Crop Productivity

Real-time pollinator monitoring enables precision pollination management in commercial agriculture. RFID tracking data quantify individual bee flower visitation rates, revealing that optimal pollination requires 4-8 visits per flower for crops like almonds and blueberries. Spatial analysis identifies field zones receiving insufficient pollinator activity, guiding supplemental hive placement or habitat enhancement. Integration with crop phenology models synchronizes pollinator deployment with peak bloom periods. Thermal imaging monitors bloom progression across orchards, triggering hive introduction when 20-30% of flowers open. Economic optimization models combine pollinator monitoring data with crop yield predictions and pollination service costs, recommending cost-effective strategies balancing rental honeybee colonies, wild pollinator habitat provision, and pesticide timing restrictions.

### 4.2. Early Detection of Stress, Disease, and Exposure Risks

Continuous physiological monitoring detects sublethal stress responses hours to days before visible symptoms emerge. Elevated hemolymph glucose and lactate concentrations indicate metabolic dysregulation from neonicotinoid exposure 12-24 hours before flight impairment manifests. Acoustic signature changes precede visible Varroa mite infestations by 1-2 weeks, enabling earlier acaricide application when treatment efficacy is highest. Machine learning models trained on multi-parameter sensor data predict disease outbreaks, combining temperature variability, foraging activity decline, and acoustic pattern shifts to achieve 76-82% accuracy in forecasting American foulbrood infections 10-14 days pre-symptomatically. Pesticide exposure monitoring integrates application timing data from precision agriculture platforms with pollinator foraging patterns, generating alerts when foraging bees enter recently sprayed fields.

### 4.3. Decision Support for Conservation and Farm Management

Integrated decision support systems synthesize pollinator health data with environmental and agricultural management information. Multi-criteria optimization frameworks balance pollination services, crop productivity, pesticide use, and biodiversity conservation objectives. Adaptive management protocols incorporate real-time monitoring feedback, automatically recommending interventions including adjusting irrigation to extend bloom duration, delaying pesticide applications, or introducing supplemental pollinator species. Long-term monitoring datasets inform landscape-scale conservation planning, identifying critical habitat corridors and optimal locations for pollinator-friendly cover crops. Citizen science integration expands monitoring coverage by engaging farmers and landowners in data collection through mobile applications that guide non-experts through sensor deployment and interpretation of automated health assessments.

## 5. Challenges and Future Perspectives

### 5.1. Miniaturization, Power, and Durability Constraints

Current biosensor and tracking technologies face significant engineering challenges (Table 5). Tag mass represents a critical constraint—devices exceeding 15-20% of body mass impair flight performance and foraging efficiency. Achieving sub-100 mg total system mass while integrating sensors, wireless communication, and batteries requires continued advances in MEMS fabrication and flexible electronics. Battery life limits continuous monitoring duration, with active sensors typically operating 3-7 days before replacement. Energy harvesting from solar cells, thermoelectric generators, or piezoelectric elements could extend operational lifetime but adds mass and complexity. Environmental durability remains problematic, with outdoor deployment exposing devices to temperature extremes and mechanical stress. Biofouling of implanted sensors by hemolymph proteins degrades electrochemical sensor performance within 48-72 hours.

### 5.2. Data Privacy, Ethics, and Ecological Impact

Bio-digital monitoring raises ethical considerations regarding animal welfare and ecological intervention. Sensor attachment procedures require anesthesia, introducing stress and potential injury. Long-term device carriage may impair foraging success or alter social interactions within colonies. Ethical frameworks must balance scientific knowledge gain against individual welfare costs]. Data ownership and access present governance challenges, with commercial platforms potentially restricting data access or aggregating information across farms without individual consent. Open-data frameworks promoting transparent sharing must balance privacy concerns with collective benefit from regional-scale ecological intelligence.

### 5.3. Scalability and Long-Term Deployment

Scaling bio-digital monitoring from research prototypes to operational agricultural systems requires addressing economic, technical, and institutional barriers. Per-colony monitoring costs currently range from $500-5000, prohibitive for widespread adoption in commercial beekeeping. Standardization of data formats, communication protocols, and analytical methods is essential for interoperability across platforms and geographic regions. Long-term maintenance and calibration requirements challenge sustained deployment, with sensor drift necessitating periodic recalibration against reference standards. Institutional capacity for data interpretation and management response limits practical value, requiring training for farmers and land managers in dashboard interpretation and evidence-based decision-making.

## 6. Conclusion

Bio-digital integration technologies offer unprecedented capabilities for real-time, multi-scale monitoring of pollinator health and behavior in agricultural and natural ecosystems. Miniaturized biosensors, digital tracking systems, IoT platforms, and artificial intelligence collectively enable continuous assessment of physiological status, behavioral patterns, and stress responses undetectable through traditional approaches. Applications in precision agriculture support optimized pollination management, early disease detection, and pesticide exposure mitigation, directly contributing to crop productivity and pollinator conservation. Despite remarkable technological progress, challenges in device miniaturization, energy autonomy, data standardization, and ethical deployment require continued interdisciplinary collaboration. Future systems will integrate multi-species monitoring, incorporate genomic and metabolomic biomarkers, and leverage distributed sensor networks providing landscape-scale ecological intelligence. As pollinator populations face intensifying environmental pressures, bio-digital monitoring systems represent essential infrastructure for evidence-based conservation and sustainable food production, transforming reactive crisis management into proactive ecosystem stewardship.

## 7. Figures

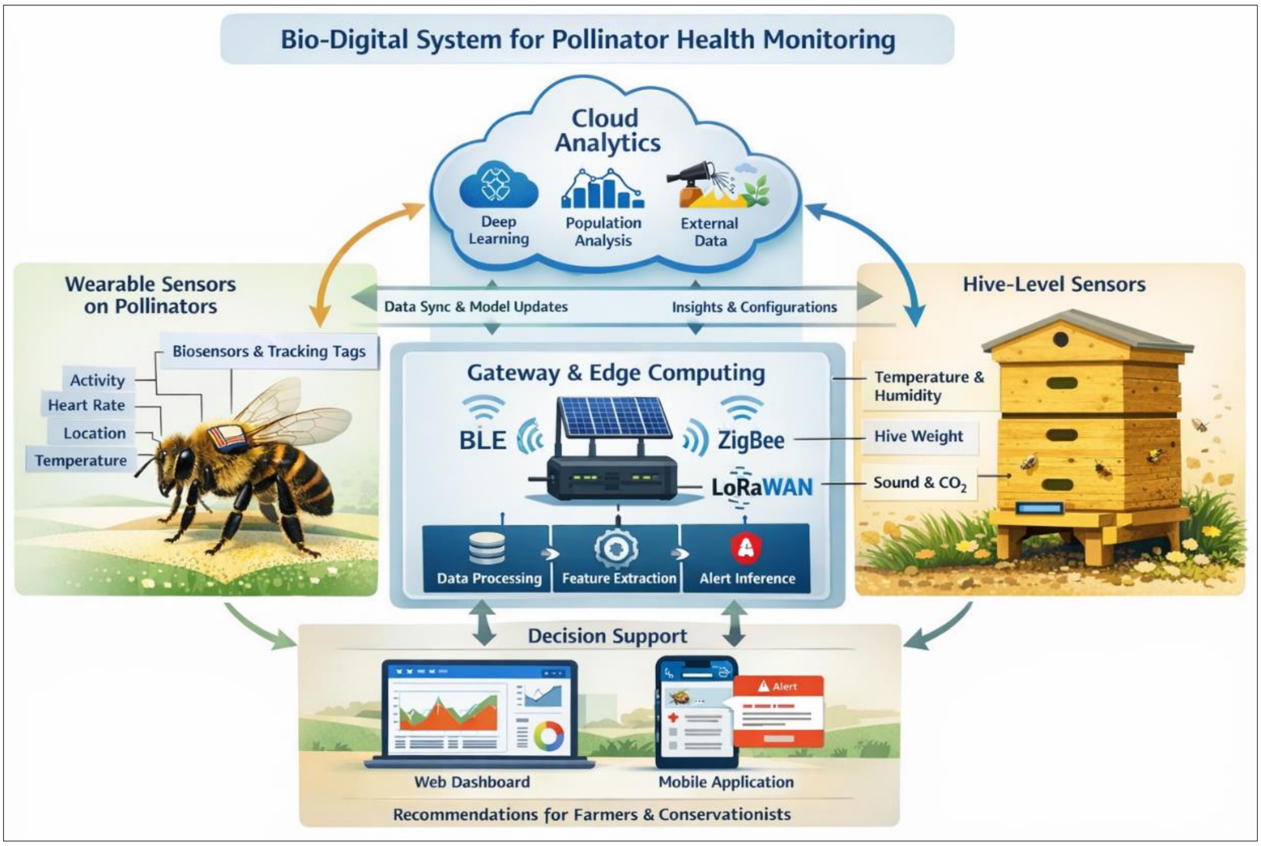


**Fig 1:** Bio-digital system architecture for real-time pollinator health monitoring.

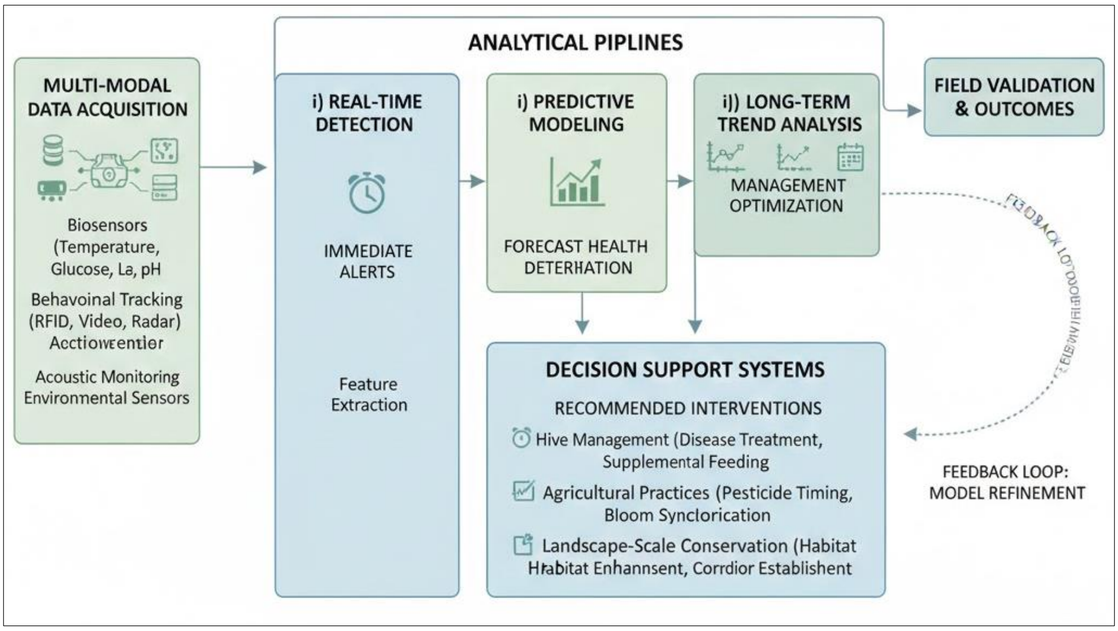


**Fig 2:** Integrated workflow combining biosensing, digital analytics, and decision-support for pollinator management.

## 8. Tables

**Table 1:** Key pollinator species and health indicators measurable using bio-digital technologies

| Species | Body Mass (mg) | Primary Health Indicators | Biosensor Compatibility | Tracking Technologies |
|---|---|---|---|---|
| *Apis mellifera* (Honeybee) | 80-100 | Hemolymph glucose, lactate, temperature, wingbeat frequency, foraging duration | High – thorax attachment suitable for multi-sensor arrays | RFID, harmonic radar, optical tracking, GPS (queens) |
| *Bombus terrestris* (Bumblebee) | 200-400 | Temperature, flight kinematics, foraging efficiency, nest attendance | Moderate – larger tags tolerated but colony size limits sample numbers | RFID, harmonic radar, miniaturized GPS |
| *Bombus impatiens* (Common Eastern Bumblebee) | 150-250 | Metabolic rate, thermoregulation, pesticide-induced flight impairment | Moderate – similar to B. terrestris | RFID, harmonic radar, video tracking |
| *Osmia lignaria* (Mason bee) | 30-50 | Nesting behavior, provisioning rate, developmental timing | Low – mass constraints limit sensor options | Passive RFID (minimal mass tags), optical nest monitoring |
| *Megachile rotundata* (Alfalfa leafcutter bee) | 40-60 | Cell provisioning rate, parasitism incidence, emergence timing | Low – primarily behavioral metrics via nest monitoring | Optical tracking, nest-box sensors (temperature, humidity) |

**Table 2:** Biosensors and wearable/implantable devices used for monitoring pollinator physiology and behavior

| Sensor Type | Measured Parameters | Detection Principle | Mass (mg) | Operating Duration | Validation Status |
|---|---|---|---|---|---|
| Electrochemical microsensor | Glucose, lactate, oxidative stress markers | Enzymatic reaction generating current signal | 15-30 | 48-72 hours (biofouling limited) | Laboratory validated; limited field deployment |
| Thermocouple/thermistor | Body and hemolymph temperature | Resistance change with temperature | 5-12 | Continuous (passive) or months (active with battery) | Extensively field-deployed |
| Optical wingbeat sensor | Wingbeat frequency, amplitude modulation | Reflected infrared light modulation | 20-35 | 3-7 days (battery) | Field validated in multiple studies |
| Acoustic sensor (on-body) | Flight buzzing, communication signals | Piezoelectric or MEMS microphone | 25-40 | 2-5 days (battery) | Prototype stage; promising initial results |
| Accelerometer/gyroscope (IMU) | Flight kinematics, activity state | MEMS inertial measurement | 30-50 | 3-7 days (battery) | Laboratory and field validated |
| pH microsensor | Hemolymph acid-base status | Ion-selective electrode or optical fluorescence | 10-20 | 24-48 hours | Laboratory validation only |
| Flexible multi-sensor array | Temperature, pH, electrolytes ($Na^+$, $K^+$) | Polymer substrate with integrated sensors | 40-60 | 48-96 hours | Early development; proof-of-concept |

**Table 3:** Digital tracking, communication, and data acquisition technologies for pollinator monitoring

| Technology | Spatial Resolution | Range | Individual ID Capability | Data Throughput | Power Consumption | Primary Applications |
|---|---|---|---|---|---|---|
| Passive RFID | 1-5 cm | 0.1-2 m | Yes (unique tag ID) | Low (presence/absence) | None (passive backscatter) | Hive entrance/exit monitoring, nest box tracking |
| Active RFID | 1-10 cm | 10-1000 m | Yes | Moderate (ID + timestamp) | 10-50 mW (limits battery life) | Landscape-scale foraging tracking |
| Harmonic radar | 5-50 cm | 100-900 m | No (unless multiple frequencies) | Low (position only) | Passive tag + external transmitter | Flight path reconstruction, foraging range studies |
| Optical tracking (computer vision) | <1 mm | 0.5-10 m (camera field of view) | Yes (via visual markers or morphology) | High (video streams) | Moderate (camera + processing) | Behavioral ethograms, hive entrance activity, flight kinematics |
| Miniaturized GPS | 2-10 m (open sky) | Global | Yes | Moderate (coordinates + timestamp) | 100-300 mW (major constraint) | Large bee species, long-distance tracking |
| Bluetooth Low Energy (BLE) beacons | 1-5 m | 10-100 m | Yes | Moderate (ID + RSSI proximity) | 1-10 mW | Indoor/outdoor transition tracking, hive proximity monitoring |
| LoRaWAN | N/A (connectivity, not positioning) | 2-15 km | Yes (node ID) | Low (suitable for sensor data) | <50 mW | Environmental sensors, remote hive monitoring |

**Table 4:** Data analytics and AI methods applied to pollinator health assessment

| Method Category | Specific Algorithms | Input Data Types | Outputs | Computational Requirements | Deployment Location |
|---|---|---|---|---|---|
| Classical machine learning | Random forest, SVM, k-NN | Extracted features (foraging rate, temperature statistics, acoustic features) | Binary classification (healthy/diseased), exposure level | Low-moderate; edge-compatible | Edge and cloud |
| Deep learning – CNNs | ResNet, MobileNet, EfficientNet | Images (thermal, visible, nest box cameras) | Object detection (bees, parasites), health classification | High; typically cloud or GPU edge | Cloud (training); edge (inference with optimized models) |
| Deep learning – RNNs/LSTMs | LSTM, GRU, Temporal CNNs | Time-series sensor data (temperature, accelerometer, biosensors) | State prediction, anomaly detection, collapse forecasting | Moderate-high; edge deployment feasible with quantization | Cloud and optimized edge |
| Autoencoders | Variational autoencoders, denoising autoencoders | Multi-modal sensor streams | Anomaly detection, dimensionality reduction, missing data imputation | Moderate | Cloud and edge |
| Bayesian methods | Bayesian networks, Gaussian processes | Multi-sensor fusion, uncertain measurements | Probabilistic health scores, confidence intervals | Low-moderate | Edge and cloud |
| Signal processing | Wavelet transforms, Fourier analysis, Kalman filtering | Acoustic, temperature, acceleration time series | Feature extraction, noise reduction, trajectory smoothing | Low; highly edge-compatible | Edge |
| Clustering & dimensionality reduction | k-means, DBSCAN, PCA, t-SNE | High-dimensional sensor data | Behavioral state segmentation, pattern discovery | Low-moderate | Cloud (exploratory); edge (predefined clusters) |

**Table 5:** Advantages, limitations, and ethical considerations of bio-digital monitoring systems for pollinators

| Dimension | Advantages | Limitations | Ethical Considerations |
|---|---|---|---|
| Temporal resolution | Continuous monitoring (seconds to months); captures acute stress responses and circadian patterns invisible to manual surveys | Battery life and sensor durability restrict long-term continuous operation; data gaps during device failure or maintenance | Continuous tracking may constitute excessive surveillance; balance information gain against animal welfare |
| Spatial coverage | Scalable to landscape level via distributed sensors; tracks individual movements across heterogeneous environments | High deployment costs limit density; communication range constrains spatial extent; GPS ineffective indoors/under canopy | Potential habitat disturbance during sensor installation; electromagnetic pollution concerns |
| Physiological insight | Direct measurement of biomarkers (glucose, lactate, temperature) reveals mechanistic stress responses | Invasive sensor attachment; biofouling degrades performance; limited biomarker panel compared to laboratory analysis | Anesthesia and attachment procedures cause stress and potential injury; long-term device carriage may impair fitness |
| Behavioral detail | High-resolution tracking of foraging, social interactions, navigation; quantifies sublethal pesticide effects | Video analysis computationally intensive; optical tracking limited to restricted spaces; RFID requires proximity to readers | Marked individuals may experience altered social status; potential for differential survival biasing population inferences |

| | | | |
|---|---|---|---|
| Early warning capability | Predictive models detect disease and stress days-to-weeks pre-symptomatically; enables proactive intervention | Prediction accuracy depends on training data quality and representativeness; false positives may trigger unnecessary actions | Premature or excessive intervention could disrupt colony homeostasis; balance precaution with ecological autonomy |
| Data integration | Combines multiple information streams (physiological, behavioral, environmental) for holistic health assessment | Data heterogeneity complicates integration; lack of standardization hinders cross-platform compatibility | Data ownership ambiguities; commercial platforms may restrict access or monetize farmer/researcher data without consent |
| Automation & scalability | Reduces labor compared to manual inspection; AI enables analysis of massive datasets infeasible for humans | Requires technical expertise for deployment and interpretation; infrastructure costs (edge/cloud computing) | Digital divide may exclude small-scale or resource-limited stakeholders; risk of technology reinforcing inequalities |
| Real-time decision support | Immediate alerts enable timely intervention (pesticide exposure mitigation, disease treatment, hive relocation) | Communication latency in remote areas; over-reliance on automated recommendations may undermine expert judgment | Responsibility attribution when AI recommendations lead to negative outcomes; need for human-in-the-loop decision frameworks |

## 9. References


1. Ollerton J, Winfree R, Tarrant S. How many flowering plants are pollinated by animals? Oikos. 2011;120(3):321-6.
2. Klein AM, Vaissiere BE, Cane JH, Steffan-Dewenter I, Cunningham SA, Kremen C, *et al*. Importance of pollinators in changing landscapes for world crops. Proc R Soc B. 2007;274(1608):303-13.
3. Lautenbach S, Seppelt R, Liebscher J, Dormann CF. Spatial and temporal trends of global pollination benefit. PLoS One. 2012;7(4):e35954.
4. Garibaldi LA, Steffan-Dewenter I, Winfree R, Aizen MA, Bommarco R, Cunningham SA, *et al*. Wild pollinators enhance fruit set of crops regardless of honey bee abundance. Science. 2013;339(6127):1608-11.
5. Potts SG, Biesmeijer JC, Kremen C, Neumann P, Schweiger O, Kunin WE. Global pollinator declines: trends, impacts and drivers. Trends Ecol Evol. 2010;25(6):345-53.
6. vanEngelsdorp D, Hayes J Jr, Underwood RM, Pettis J. A survey of honey bee colony losses in the U.S., fall 2007 to spring 2008. PLoS One. 2008;3(12):e4071.
7. Biesmeijer JC, Roberts SPM, Reemer M, Ohlemuller R, Edwards M, Peeters T, *et al*. Parallel declines in pollinators and insect-pollinated plants in Britain and the Netherlands. Science. 2006;313(5785):351-4.
8. Goulson D, Nicholls E, Botias C, Rotheray EL. Bee declines driven by combined stress from parasites, pesticides, and lack of flowers. Science. 2015;347(6229):1255957.
9. Doublet V, Labarussias M, de Miranda JR, Moritz RFA, Paxton RJ. Bees under stress: sublethal doses of a neonicotinoid pesticide and pathogens interact to elevate honey bee mortality across the life cycle. Environ Microbiol. 2015;17(4):969-83.
10. Lebuhn G, Droege S, Connor EF, Gemmill-Herren B, Potts SG, Minckley RL, *et al*. Detecting insect pollinator declines on regional and global scales. Conserv Biol. 2013;27(1):113-20.
11. Henry M, Beguin M, Requier F, Rollin O, Odoux JF, Aupinel P, *et al*. A common pesticide decreases foraging success and survival in honey bees. Science. 2012;336(6079):348-50.
12. Carvell C, Roy DB, Smart SM, Pywell RF, Preston CD, Goulson D. Declines in forage availability for bumblebees at a national scale. Biol Conserv. 2006;132(4):481-9.
13. Colin T, Meikle WG, Wu X, Barron AB. Traces of a neonicotinoid induce precocious foraging and reduce foraging performance in honey bees. Environ Sci Technol. 2019;53(14):8252-61.
14. Sponsler DB, Johnson RM. Honey bee success predicted by landscape composition in Ohio, USA. PeerJ. 2015;3:e838.
15. Kammer AE, Heinrich B. Insect flight metabolism. Adv Insect Physiol. 1978;13:133-228.
16. Zebelo SA, Maffei ME. Role of early signalling events in plant-insect interactions. J Exp Bot. 2015;66(2):435-48.
17. Stabentheiner A, Kovac H, Brodschneider R. Honeybee colony thermoregulation - regulatory mechanisms and contribution of individuals in dependence on age, location and thermal stress. PLoS One. 2010;5(1):e8967.
18. Churcher B, Mak JCY, Zhao L, Hamilton JGC. Miniature respirometry system for measuring metabolic rate in insects. J Insect Physiol. 2017;102:102-10.
19. Schneider SS, Hoffman GD, Smith DR. The African honey bee: factors contributing to a successful biological invasion. Annu Rev Entomol. 2004;49:351-76.
20. Ferrari MC, Wisenden BD, Chivers DP. Chemical ecology of predator-prey interactions in aquatic ecosystems: a review and prospectus. Can J Zool. 2010;88(7):698-724.
21. Chen C, Yang EC, Jiang JA, Lin TT. An imaging system for monitoring the in-and-out activity of honey bees. Comput Electron Agric. 2012;89:100-9.
22. Tautz J, Maier S, Groh C, Rossler W, Brockmann A. Behavioral performance in adult honey bees is influenced by the temperature experienced during their pupal development. Proc Natl Acad Sci U S A. 2003;100(12):7343-7.
23. Riley JR, Smith AD, Reynolds DR, Edwards AS, Osborne JL, Williams IH, *et al*. Tracking bees with harmonic radar. Nature. 1996;379(6560):29-30.
24. Streit S, Bock F, Pirk CWW, Tautz J. Automatic life-long monitoring of individual insect behaviour now possible. Zoology (Jena). 2003;106(3):169-71.
25. Degen J, Kirbach A, Reiter L, Lehmann K, Norton P, Storms M, *et al*. Exploratory behaviour of honeybees during orientation flights. Anim Behav. 2015;102:45-57.
26. Campbell JW, Cabrera AR, Stanley-Stahr C, Ellis JD. An evaluation of the honey bee (Hymenoptera: Apidae) waggle dance as a foraging site communication mechanism in Florida orange groves. Environ Entomol. 2016;45(2):473-81.
27. Sledevič T. The application of convolutional neural network for pollen bearing bee classification. In: 2018 IEEE 6th Workshop on Advances in Information, Electronic and Electrical Engineering (AIEEE); 2018 Nov 8-10; Vilnius, Lithuania. Piscataway: IEEE; 2018. p. 1-4.