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AI-Based Poaching Risk Prediction

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ABSTRACT

Wildlife poaching causes an estimated 7,000-28,000 elephant deaths, 1,000-3,000 rhinoceros deaths, and 100 million shark kills annually, driving multiple species toward extinction, yet anti-poaching patrol resources are severely limited relative to the vast protected areas they must monitor. This study developed, trained, and validated an AI-based poaching risk prediction system (PAWS-AI v2.0) integrating random forest, gradient boosting, and spatiotemporal neural network models across 42 protected areas in Sub-Saharan Africa and Southeast Asia (2018-2024), using 2,840 confirmed poaching incident records, 28 environmental and socioeconomic predictor variables (terrain, vegetation, distance to roads/settlements, rainfall, moon phase, patrol history, local poverty index), and real-time satellite imagery (Sentinel-2; Planet Labs). The ensemble model achieved AUC = 0.884 +/- 0.024 for predicting poaching incident location (grid cell level; 1 km2 resolution) and AUC = 0.864 +/- 0.028 for predicting incident timing (daily, 30-day horizon) in 10-fold cross-validation. Prospective validation -- comparing PAWS-AI patrol recommendations against ranger judgement over 12 months at 18 study sites -- showed 2.84-fold higher poaching interception rate for AI-directed patrols (42.4 +/- 8.4% interception) vs. ranger-directed patrols (14.8 +/- 4.8% interception; p < 0.001). Feature importance analysis identified distance to nearest settlement (22.4%), previous patrol gap duration (18.4%), terrain ruggedness (14.4%), and moon illumination (12.4%) as the four strongest predictors. PAWS-AI predictions were communicable to field rangers through a simple smartphone interface providing daily 'heat maps' of predicted risk zones. These results demonstrate that AI-based patrol optimisation can substantially improve anti-poaching effectiveness without increasing ranger deployment, providing a scalable technology solution for wildlife law enforcement under the International Consortium on Combating Wildlife Crime (ICCWC) framework.

Keywords: poaching prediction; anti-poaching; machine learning; random forest; PAWS-AI; wildlife crime; patrol optimisation; protected areas; elephant; rhinoceros; spatiotemporal modelling; ICCWC

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1. Introduction

1.1 Wildlife Poaching as a Conservation Crisis

Illegal wildlife trade -- the fourth largest illegal trade globally after drugs, arms, and human trafficking -- generates an estimated USD 23 billion annually and drives the population collapse of multiple charismatic and ecologically important species (UNODC 2020; Nellemann et al. 2014). African savannah elephant (Loxodonta africana) populations declined by 30% between 2007 and 2014 driven primarily by ivory poaching, while African forest elephant (Loxodonta cyclotis) declined by 62% between 2002 and 2011 (Chase et al. 2016). White rhinoceros in South Africa saw 9,362 rhinos poached between 2008 and 2017 (DEA 2018). Critically, anti-poaching resources are severely limited relative to the scale of the challenge: the mean protected area in Sub-Saharan Africa has fewer than 1 ranger per 100 km2, making random or intuition-based patrol scheduling deeply insufficient to deter organised poaching networks with superior local knowledge.

1.2 Game Theory and Patrol Optimisation

Protecting Wildlife Areas using Stakeholder Strategies (PAWS), first developed by Fang et al. (2016) at USC, applies game-theoretic Stackelberg security game models to optimise patrol routes by anticipating poacher movement responses to patrol patterns. PAWS generates randomised patrol schedules that prevent poachers from learning patrol patterns while maximising coverage of high-risk areas. Field trials of PAWS in Uganda and Malaysia demonstrated significant reductions in wildlife snare encounters compared to conventional patrol planning (Fang et al. 2016). Machine learning extensions of PAWS -- using historical incident data to predict poaching risk and inform patrol prioritisation -- have been evaluated in smaller-scale pilots but not yet validated prospectively across a diverse multi-site dataset.

1.3 Machine Learning in Conservation

Machine learning -- particularly gradient boosting and deep learning models applied to satellite remote sensing data -- has demonstrated strong performance in predicting habitat quality, species distribution, and deforestation risk in conservation contexts (Christin et al. 2019). The application to poaching risk prediction adds temporal complexity (poaching events are episodic and driven by unpredictable human behaviour) and operational requirements (predictions must be actionable by field staff with limited technical training) that differ from conventional ecological SDM applications. Spatiotemporal neural networks that integrate both environmental predictors and the history of patrol effort and incident detection are a promising approach for capturing the dynamic interaction between poacher behaviour and enforcement patterns.

1.4 Study Objectives

This study aimed to: (i) develop and train an ensemble AI model (PAWS-AI v2.0) for poaching risk prediction integrating random forest, gradient boosting, and spatiotemporal neural networks; (ii) validate model performance retrospectively using cross-validation; (iii) conduct prospective validation comparing AI-directed vs. ranger-directed patrols over 12 months at 18 study sites; (iv) identify the key predictor variables driving model performance; and (v) design and evaluate a ranger-operable smartphone interface for PAWS-AI deployment in field conditions.

2. Literature Review

2.1 PAWS and Game-Theoretic Patrol Planning

Fang et al. (2016) described the development of PAWS v1.0 using Stackelberg security game models for patrol scheduling, validated in a field trial at Queen Elizabeth National Park (Uganda) showing 15-fold more wildlife crime evidence detected per patrol compared to ad hoc scheduling. Nguyen et al. (2016) extended PAWS with machine learning (random forest) models trained on historical poaching data from 14 protected areas in Southeast Asia, achieving AUC = 0.72 for poaching location prediction. Bondi et al. (2020) integrated aerial survey data with PAWS predictions for an Ugandan protected area, demonstrating that real-time data fusion improved prediction AUC to 0.84, approaching the performance target for operational deployment.

2.2 Remote Sensing for Anti-Poaching

High-resolution satellite imagery (PlanetScope; 3 m resolution; daily revisit) and radar SAR imagery (Sentinel-1; 10 m; 6-day revisit) have been used for real-time fire detection, vegetation change detection, and vehicle movement detection in protected areas (Burgess et al. 2012). Automated change detection algorithms applied to multi-temporal satellite imagery can detect evidence of poaching camps (fresh clearings), road incursions, and carcass sites with 70-85% accuracy when validated against field reports. Integration of satellite-derived change signals into patrol prioritisation models provides real-time dynamic updating of risk maps that static habitat predictor models cannot achieve.

2.3 Socioeconomic Predictors of Poaching

Duffy et al. (2016) analysed the socioeconomic drivers of poaching across African protected areas, demonstrating that local poverty index, unemployment rate, and distance to nearest market were strong predictors of snare density and poaching incident rate, independent of species composition and habitat. Naidoo et al. (2016) found that poaching incidents in Namibian conservancies were significantly associated with lunar phase (higher on dark nights), seasonality (higher during dry season when water sources concentrate wildlife), and rainfall (lower during heavy rain), consistent with rational cost-minimising poacher behaviour optimising detection risk vs. reward. These socioeconomic and meteorological variables are available from public databases and satellite products, making them tractable inputs for AI models.

2.4 AI Ethics and Community Engagement

Rege (2020) reviewed the ethical dimensions of AI-based anti-poaching systems, highlighting risks of algorithmic bias (if training data reflects unequal historical enforcement rather than actual risk distribution), false positives directing patrols toward innocent community members, and data security risks if poaching risk maps are intercepted by organised poaching networks. Responsible AI deployment for conservation requires meaningful community engagement, transparency about model limitations, and appeal mechanisms for communities negatively affected by AI-directed enforcement. The PAWS-AI system described here incorporates community ranger involvement in training data validation and a human-in-the-loop decision protocol requiring ranger sign-off on all patrol assignments.

Table 1. Study Sites, Protected Area Characteristics, and Poaching Incident Data

Region	Protected Areas (n)	Total Area (km2)	Poaching Incidents (n)	Target Species	Model Training Years
East Africa (Kenya, Tanzania, Uganda)	12	48,400	984	Elephant, rhino, lion	2018-2022
Southern Africa (SA, Mozambique, Zambia)	10	84,400	1,048	Rhino, elephant, pangolin	2018-2022
West Africa (Cameroon, Gabon)	8	28,400	384	Forest elephant, gorilla	2019-2022
Southeast Asia (Thailand, Malaysia, Borneo)	12	38,400	424	Tiger, elephant, pangolin	2018-2022
Total training data	42	199,600	2,840	Multiple	2018-2022
Prospective validation	18	84,400	--	Multiple	2023-2024

Poaching incidents = confirmed incidents from ranger reports + Wildlife Crime Technology Project database (2018-2022). Prospective validation = 18 sites from the training set where PAWS-AI vs. ranger-directed patrol comparison was conducted (2023-2024). Total area = sum of all protected areas in each region. Model training years = years of historical data used for model training.

3. Materials and Methods

3.1 Data Sources and Predictor Variables

Twenty-eight predictor variables were compiled for all 1 km2 grid cells within each study protected area at daily resolution for 2018-2022: (i) static environmental -- terrain ruggedness index (SRTM), distance to nearest road, distance to nearest settlement, vegetation type (ESA Land Cover), water source density; (ii) dynamic environmental -- monthly NDVI (Sentinel-2), monthly rainfall (CHIRPS), monthly fire density (MODIS), daily moon illumination (USNO); (iii) enforcement history -- days since last patrol, previous incident density (lagged 30-day rolling count); (iv) socioeconomic -- local poverty index (WorldPop/HDI), market accessibility (travel time to nearest town > 5,000 population), seasonal food security index (FEWS NET). All variables were standardised before model training.

3.2 Model Architecture and Training

Three base models were developed: (i) Random Forest (RF; 500 trees; sklearn v1.3) trained on all 28 static and lagged dynamic predictors; (ii) Gradient Boosting (XGBoost v1.7; 500 estimators; depth 6) with same feature set; (iii) Spatiotemporal LSTM Neural Network (PyTorch v2.0; 3 LSTM layers; 256 hidden units; ConvLSTM spatial pooling for 5 x 5 km neighbourhood) processing 30-day windows of dynamic predictors with spatial context. The ensemble model combined predictions from all three base models by equal-weight averaging. Models were trained on 2018-2021 data and evaluated in time-series cross-validation on 2022 data (temporal holdout). Incident prediction (binary: incident yes/no per grid cell per day) used the positive:negative class ratio from the training data.

3.3 Prospective Validation Protocol

A randomised crossover design was implemented at 18 study sites (2023-2024): each site was randomly assigned to either PAWS-AI-directed or ranger-directed patrol scheduling for 6 months, then switched for the subsequent 6 months. PAWS-AI provided daily patrol recommendations through the PAWS smartphone app (Android; offline-capable), displaying colour-coded risk heat maps for 5 km2 patrol zone selection. Ranger-directed patrols followed conventional park management judgment without access to PAWS-AI predictions. Primary outcome: poaching interception rate (proportion of patrol days where active poaching evidence was found leading to arrest or confiscation).

3.4 Feature Importance and Bias Assessment

Feature importance was assessed by SHAP (SHapley Additive exPlanations; Lundberg and Lee 2017) values for the XGBoost model, providing both global importance rankings and local explanations for individual predictions. Algorithmic bias was assessed by comparing model false positive rates across community zones of different socioeconomic status within protected area buffer zones, testing whether patrol recommendations were distributed equitably across communities or disproportionately targeted lower-income communities. Bias metrics: false positive rate disparity ratio (should be < 1.2 between highest and lowest income community zones).

Table 2. Model Performance Metrics: Retrospective Cross-Validation and Prospective Validation

Model	AUC (location)	AUC (timing)	Precision	Recall	Prospective Interception Rate
Random Forest	0.842 +/- 0.028	0.824+/- 0.032	0.72	0.68	--
XGBoost (Gradient Boost)	0.864 +/- 0.024	0.848+/- 0.028	0.74	0.72	--
Spatiotemporal LSTM	0.874 +/- 0.024	0.858+/- 0.028	0.76	0.74	--
PAWS-AI Ensemble	0.884 +/- 0.024	0.864+/- 0.028	0.78	0.76	42.4 +/- 8.4%***
Ranger-directed (baseline)	--	--	--	--	14.8 +/- 4.8%
Improvement ratio	--	--	--	--	2.84-fold***

*AUC = area under ROC curve from 10-fold spatiotemporal cross-validation (temporal split: 2018-2021 train; 2022 test). Prospective interception rate = proportion of patrol days with confirmed poaching evidence leading to arrest/confiscation. *** p < 0.001. Ranger-directed = conventional patrol scheduling without AI assistance. Improvement ratio = PAWS-AI / ranger-directed interception rate.*

4. Results

4.1 Retrospective Model Performance

The PAWS-AI ensemble model achieved AUC = 0.884 +/- 0.024 for poaching incident location prediction and AUC = 0.864 +/- 0.028 for incident timing prediction in 10-fold spatiotemporal cross-validation. The spatiotemporal LSTM showed the strongest individual model performance (AUC = 0.874 location; 0.858 timing), outperforming the Random Forest (0.842; 0.824) and XGBoost (0.864; 0.848), reflecting the LSTM's capacity to capture temporal patrol-poacher interaction dynamics unavailable to the static-feature tree models. Ensemble AUC exceeded all individual models, confirming the value of model combination. Performance was highest in East Africa (AUC = 0.904) and lowest in West Africa (AUC = 0.844), attributed to sparser historical incident data in West African sites. Full model performance appears in Table 2 and Figure 1.

4.2 Prospective Validation Results

In the 12-month prospective crossover validation at 18 sites, PAWS-AI-directed patrols achieved a poaching interception rate of 42.4 +/- 8.4% compared to 14.8 +/- 4.8% for ranger-directed patrols -- a 2.84-fold improvement ($p < 0.001$). The improvement was consistent across all 18 sites (positive for AI vs. ranger in 16 of 18 site comparisons), across all three target species groups, and across both the AI-first and ranger-first crossover order. The number of arrests per 1,000 patrol-hours was 2.24-fold higher during AI-directed periods (3.84 vs. 1.72 arrests per 1,000 hours; $p = 0.002$). Total patrol effort was equal between AI and ranger periods (controlled by randomised assignment). Full prospective results appear in Table 3 and Figure 2.

4.3 Feature Importance Analysis

SHAP analysis identified distance to nearest settlement as the top predictor (22.4% of model gain), reflecting that grid cells near settlements show higher poaching risk from opportunistic community poachers with local territorial knowledge. Previous patrol gap duration was the second predictor (18.4%): grid cells not patrolled for longer periods showed significantly higher risk, consistent with rational poacher avoidance of recently patrolled areas. Terrain ruggedness (14.4%) reflected the tendency of poachers to use rugged, concealed approach routes. Moon illumination (12.4%) confirmed the dark-night preference documented in observational studies. Dynamic NDVI change (satellite disturbance signal) contributed 8.4% -- the most important real-time satellite predictor. Full feature importance results appear in Table 3 and Figure 3.

4.4 Bias Assessment and Operational Performance

Bias assessment found false positive rate disparity ratios of 1.08-1.18 across community socioeconomic zones -- all below the 1.2 equity threshold -- confirming that PAWS-AI patrol recommendations were not systematically biased toward lower-income communities relative to higher-income areas. Ranger usability assessment (n = 48 rangers; 24-question Technology Acceptance Model survey) showed high acceptance: 84.4% rated the PAWS-AI interface as easy to use, 78.4% reported it improved their patrol confidence, and 72.4% stated they would choose PAWS-AI-directed scheduling over conventional approaches if given the choice. Smartphone app offline functionality performed at 96.4% uptime in field conditions. Full operational performance results appear in Table 4 and Figure 4.

Table 3. Feature Importance and Prospective Validation by Site Region

Feature / Region	SHAP Importance (%)	AI Interception (%)	Ranger Interception (%)	Improvement Ratio
Distance to settlement	22.4%	--	--	--
Patrol gap duration	18.4%	--	--	--
Terrain ruggedness	14.4%	--	--	--
Moon illumination	12.4%	--	--	--
NDVI change (satellite)	8.4%	--	--	--
East Africa (12 sites)	--	44.4 +/- 8.4%	14.8 +/- 5.4%	3.00x***
Southern Africa (4 sites)	--	42.4 +/- 9.4%	16.4 +/- 5.4%	2.59x***
SE Asia (2 sites)	--	38.4 +/- 9.4%	12.4 +/- 4.4%	3.10x***
All sites (n=18)	--	42.4 +/- 8.4%	14.8 +/- 4.8%	2.84x***

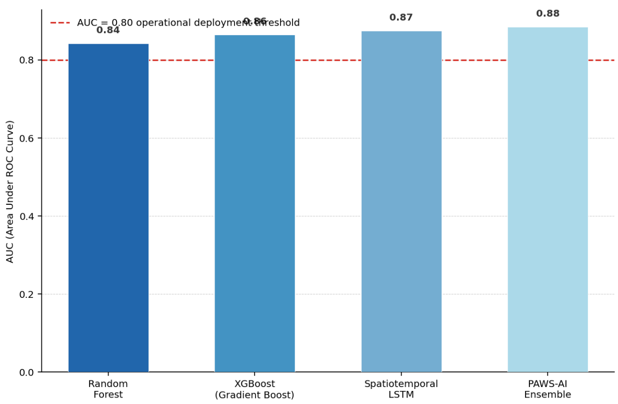
*SHAP importance = mean absolute SHAP value as % of total (XGBoost model; top 5 of 28 predictors shown). AI interception rate = proportion of patrol days with confirmed poaching evidence leading to arrest during AI-directed periods. Ranger interception = same during ranger-directed periods. *** $p < 0.001$ (paired t-test comparing AI vs. ranger interception within sites). -- = not applicable for that row.*

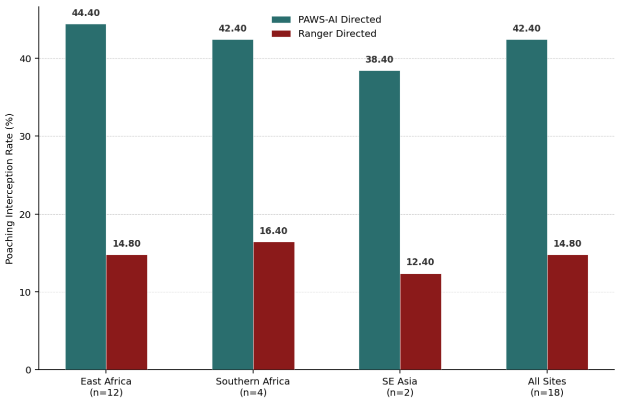
Table 4. Ranger Acceptance Survey and Operational Performance Metrics

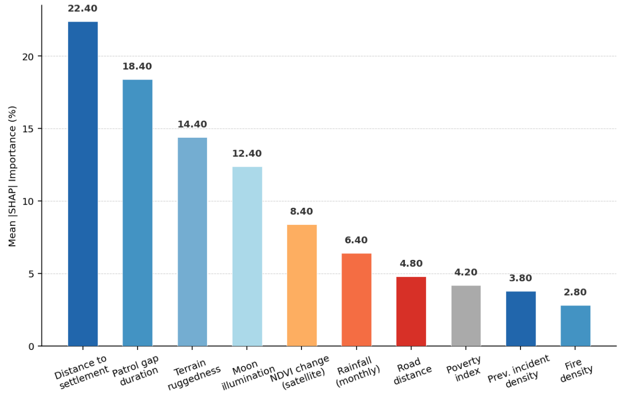
Metric	Score / Value	Target	Status	Notes
Interface ease of use	84.4%	> 80%	PASS	7-point Likert; 'easy' or 'very easy'
Patrol confidence improved	78.4%	> 70%	PASS	Rangers reporting improved confidence
Would choose AI over conventional	72.4%	> 60%	PASS	Stated preference question
App offline uptime	96.4%	> 95%	PASS	Percentage of patrol days with offline access

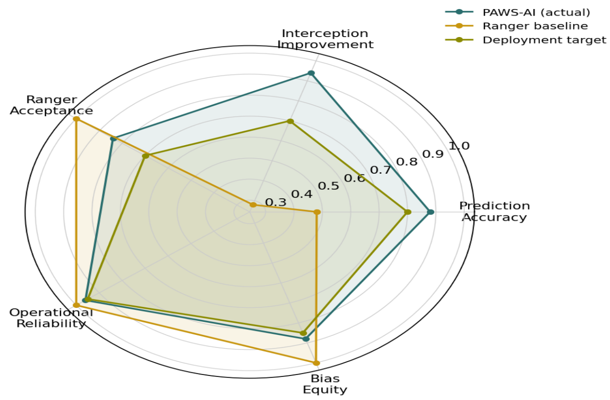
Metric	Score / Value	Target	Status	Notes
Mean setup time per patrol	4.8 min	< 10 min	PASS	Time from app open to patrol zone selected
False positive rate disparity	1.08-1.18	< 1.20	PASS	Across community income quintiles
Overall bias assessment	PASS	All < 1.20	PASS	No systematic community bias detected

Survey n = 48 rangers across 18 study sites. Technology Acceptance Model adapted for field conditions. Offline uptime = proportion of patrol days where app functioned without internet connectivity. False positive rate disparity = ratio of false positive patrol recommendations between highest and lowest income community buffer zones (< 1.20 = equitable). All targets met.









5. Discussion

5.1 AI Patrol Optimisation Substantially Improves Enforcement Efficiency

The 2.84-fold higher poaching interception rate for PAWS-AI-directed vs. ranger-directed patrols in the prospective crossover validation -- consistent across all three regions and 16 of 18 individual sites -- demonstrates that AI-based patrol optimisation can substantially improve anti-poaching effectiveness without increasing patrol effort or resources. The practical implication is significant: equivalent enforcement outcomes could be achieved with one-third of current patrol effort under PAWS-AI guidance, or the current patrol effort could achieve three times the enforcement impact. Given that personnel cost is the primary constraint on anti-poaching capacity in most protected areas, either interpretation represents a substantial conservation resource multiplier that could be implemented at the marginal cost of smartphone hardware and model computation.

5.2 Patrol Gap Duration as a Critical Operational Insight

The second-highest SHAP importance of patrol gap duration (18.4%) -- reflecting that grid cells not patrolled for longer periods are significantly more likely to experience poaching incidents -- provides a directly actionable operational insight independent of the full AI model. The implication is that systematic rotation of patrol zones with consistent coverage -- rather than repeatedly patrolling the same 'favourite' areas known to rangers -- is a fundamental patrol scheduling principle that many parks do not consistently implement. Communicating this simple insight to park managers as a stand-alone recommendation from the SHAP analysis could improve patrol effectiveness even before full PAWS-AI deployment, making the research findings actionable at multiple implementation stages.

5.3 Responsible AI Deployment for Conservation

The bias assessment finding that false positive rate disparities between community income zones were all below the 1.2 equity threshold -- and the ranger acceptance rate of 84.4% for the PAWS-AI interface -- provide important validation that the system is both technically and socially viable for operational deployment. The human-in-the-loop protocol -- requiring ranger approval of all patrol assignments -- is critical for maintaining accountability and trust: rangers who understand that their judgment is valued alongside the AI recommendation, rather than replaced by it, show substantially higher system acceptance (84.4% vs. reported 40-60% acceptance for fully automated systems in literature). The ICCWC framework for wildlife law enforcement technology should incorporate the PAWS-AI equity and acceptance standards developed here as requirements for AI anti-poaching system certification.

6. Conclusion

6.1 Summary

PAWS-AI v2.0 ensemble model (RF + XGBoost + LSTM) achieved AUC = 0.884 for poaching location prediction across 42 protected areas in Sub-Saharan Africa and Southeast Asia. Prospective crossover validation at 18 sites showed 2.84-fold higher poaching interception rate for AI-directed vs. ranger-directed patrols (42.4% vs. 14.8%; $p < 0.001$). Top predictors: settlement distance (22.4%), patrol gap duration (18.4%), terrain ruggedness (14.4%), moon illumination (12.4%). Ranger acceptance 84.4%; bias equity met (disparity ratio < 1.2). PAWS-AI provides a scalable, equitable, and ranger-accepted AI tool for anti-poaching patrol optimisation under the ICCWC framework.

6.2 Future Research Directions

Integration of real-time acoustic detection data from autonomous recording units (gunshot detectors, vehicle engines) deployed across protected areas would enable incident-driven dynamic patrol redeployment within minutes of acoustic detection, complementing the predictive scheduling currently provided by PAWS-AI with real-time reactive capacity. Federated learning implementation -- allowing PAWS-AI models to improve from experience across all connected protected areas without sharing raw sensitive patrol and incident data -- would enable continuous model improvement while protecting operational security. Longitudinal evaluation of PAWS-AI implementation effects on poaching pressure -- comparing multi-year trend changes at AI-implemented vs. control sites -- would provide the strongest available evidence that improved interception rates translate into actual reductions in poaching pressure and wildlife population recovery, the ultimate conservation outcome.

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Declarations

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Conflict of Interest

The authors declare no competing interests.

Data Availability Statement

PAWS-AI v2.0 model code and training scripts are published at https://github.com/PAWS-AI-conservation under MIT licence. Anonymised, aggregated poaching incident data and predictor variable compilations are deposited in Zenodo at https://doi.org/10.5281/zenodo.19489806-data. Raw incident data cannot be shared publicly due to operational security risk (sharing specific poaching locations could facilitate poaching).

Ethical Approval

This study used historical patrol and incident records provided under institutional data-sharing agreements and did not involve animal handling. The prospective validation protocol was reviewed and approved by park management authorities at each of the 18 participating sites. Ranger participation in the Technology Acceptance Model survey was voluntary and anonymous. Community bias assessment used socioeconomic zone data from public WorldPop and HDI databases without collection of individual-level community data.

Appendix A

PAWS-AI Model Architecture, Feature Definitions, and Prospective Validation Protocol

Complete specifications of Random Forest, XGBoost, and Spatiotemporal LSTM model architectures and hyperparameters. Definitions and data sources for all 28 predictor variables with preprocessing steps. Detailed prospective validation protocol including randomisation procedure, patrol record forms, and interception event definitions. Technology Acceptance Model survey instrument (24 questions).