ZAMBIA INFORMATION COMMUNICATION TECHNOLOGY (ICT) JOURNAL

Volume 9 (Issue 2) (2025) Pages 6-12

Using Artificial Intelligence to Mitigate Monkey-Human Conflicts in Hospitality Spaces in Zambia

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ABSTRACT

This study aimed to assess the effectiveness of an Artificial Intelligence (AI)-based deterrent system in reducing monkey incursions at a hospitality establishment in Livingstone, Zambia. The research sought to understand not only the behavioural changes in the monkeys but also the perceptions of hospitality personnel regarding the system's impact on their work environment and guest experiences. The target population included free-ranging monkeys regularly intruding on the premises and 30 hospitality staff members employed at the establishment. The staff represented diverse roles, genders, and experience levels, and all had been employed for at least six months prior to the intervention. A mixed-methods approach was adopted. Quantitative data were gathered through systematic behavioural observations of monkey activity before and after system implementation. Qualitative data were collected through 30 in-depth semi-structured interviews with staff to explore their perceptions of the system's effectiveness. Data were analysed using statistical techniques and thematic content analysis, respectively. Findings revealed a substantial decrease in both the frequency and severity of monkey incursions following the installation of the AI-based deterrent. Observable monkey behaviours shifted significantly from habituated and aggressive patterns to avoidance and flight responses. Interview data indicated improved staff morale, reduced workplace stress, enhanced guest satisfaction, and a more professional atmosphere. While some participants expressed concerns about potential long-term monkey adaptation, the overall sentiment remained strongly positive. The AI-based deterrent system proved effective in mitigating human-wildlife conflict within a hospitality setting. It created a safer, more controlled work environment and contributed positively to both operational efficiency and guest experiences. The study demonstrates that intelligent, context-sensitive technologies can yield meaningful behavioural changes in non-human species while supporting human-centred hospitality operations. This contribution extends prior Zambian AI/IoT field deployments for wildlife and pest monitoring by demonstrating effective, real-time deterrence in a hospitality context near Mosi-oa-Tunya. (Halubanza et al., Low Cost IoT-Based Automated Locust Monitoring System, Kazungula, Zambia, 2023)

Keywords—artificial intelligence, human-wildlife conflict, monkey deterrent systems, hospitality industry, sustainable tourism, Livingstone Zambia

I. INTRODUCTION

Conflicts between humans and non-human primates have become an increasingly urgent global concern, particularly in regions where expanding human settlements intersect natural wildlife habitats. This is especially evident across parts of Africa, Asia, and South America, where primate species such as macaques, baboons, and vervet monkeys exhibit remarkable behavioural adaptability, enabling them to exploit urban and peri-urban environments for food, water, and shelter. A growing body of literature has documented how such interactions are particularly problematic in tourism-reliant regions, where primates disrupt hospitality operations, damage infrastructure, and, in some cases, pose risks to human safety. [1], [2] For example, in Bali, Indonesia, macaques in Ubud's Monkey Forest are reported to interact with over 1.4 million tourists annually, often engaging in food theft and exhibiting aggressive behaviour that leads to injuries and hospital admissions. [3], [4]

On the African continent, countries like Kenya and South Africa report similar patterns of human-primate conflict, especially in and around major national parks. In Amboseli National Park, Kenya, baboons and vervet monkeys frequently invade tourist lodges and camps, while in Cape Town, South Africa, baboons are known to raid homes and tourist sites, causing property damage worth millions of rand annually. [5], [6] These instances illustrate that monkey-human conflicts are neither isolated nor novel but rather part of a growing global challenge that requires sustainable, evidence-based solutions. Comparable, technology-forward deployments in Zambia show AI and mobile/IoT pipelines can translate effectively to field conditions [20], [21]. Zambia is no exception to this trend. Monkey-human conflicts are particularly prevalent in regions adjacent to national parks and conservation areas, including Mfuwe (near South Luangwa National Park), Lower Zambezi, and Kasanka. In these regions, baboons and vervet monkeys routinely invade campsites, lodges, and even farmland, resulting in economic losses and increased human-wildlife tension. However, Livingstone—Zambia's premier tourist destination and the gateway to the iconic Victoria Falls—has emerged as the epicenter of this conflict. The city attracts over 200,000 visitors annually, [6] and its dense concentration of outdoor hospitality venues makes it especially vulnerable to primate incursions. Local AI vision work in Zambia demonstrates viable edge detection models and low-cost sensing suitable for hospitality sites [22], [23].

The two species primarily involved in these conflicts in Livingstone are the vervet monkey (*Chlorocebus pygerythrus*) and the chacma baboon (*Papio ursinus*). These primates are known to engage in disruptive behaviours such as stealing food, damaging property, and occasionally threatening or alarming tourists. These interactions carry not only economic consequences evident in annual losses estimated between ZMW 20,000 and ZMW 50,000 per affected establishment but also reputational risks for Zambia's tourism sector, which contributes over 7% to the national GDP. [7] Compounding the problem are the associated public health risks. Complementary IoT waste-management can reduce food cues that draw primates [24]. Monkeys are potential vectors for zoonotic diseases, including rabies, simian foamy virus, and gastrointestinal infections, making their frequent contact with humans a serious health concern. [8] Despite these multifaceted challenges, current mitigation strategies—such as physical barriers, chemical repellents, and manual interventions remain ineffective, costly, or environmentally unsustainable. [9] Physical barriers are expensive and easily circumvented, chemicals pose ecological hazards, and hiring staff to manually deter monkeys is labour-intensive and inconsistent. Considering these limitations, this study proposes a novel, AI-driven approach that utilises motion-sensor technology paired with bio-acoustic deterrents—specifically predator sounds such as lion roars—to mitigate monkey incursions in hospitality environments.

II. METHODOLOGY

A. *Study Design*

This study employed a quasi-experimental design structured into three chronological phases: Pre-Intervention, Intervention, and Post-Intervention.

B. *Sampling and Group Formation*

A purposive sampling method was used to select a hospitality establishment located in Livingstone, Zambia. Three inclusion criteria guided the selection: (1) the presence of frequent and disruptive monkey activity, (2) proximity to Mosi-oa-Tunya National Park, and (3) the institution's willingness to participate in a full intervention study. No control site was used due to logistical limitations; however, internal consistency was ensured through systematic data collection across all three phases.

C. *Tools and Materials*

The deterrent system was built using an integrated suite of hardware, software, and AI algorithms designed to detect and deter vervet monkeys in real time. At the core was a Windows-based PC serving as the control hub, processing input from detection cameras, running classification algorithms, and triggering audio deterrents. The system allowed for remote adjustments to parameters such as response timing, volume, and frequency. Detection relied on a Convolutional Neural Network (CNN) trained on over 7,000 annotated images including both public datasets and custom field captures accurately identifying vervet monkeys through labeled bounding boxes and class identifiers. Comparable CNN pipelines (including quantized MobileNet variants) have been fielded locally with strong accuracy/latency trade-offs [22].

- D. Summary of Dataset Characteristics

Environment	Number of Images	Image Resolution	Source Type
Urban Areas	1500	1280x720	Surveillance
Forests	2000	1920x1080	Wildlife Cameras
Hospitality Zones	2500	1280x720	CCTV/Smartphones
Mixed Environments	1000	Various	Mixed

Each image and video frame were annotated to indicate whether a monkey was present and to mark its location. Annotation was performed using open-source tools such as Labelling.

D. *Data Augmentation*

To increase the effective size of the training dataset and improve model generalization, several data augmentation techniques were employed. These methods helped simulate real-world variability in pose, lighting, and background. Table II shows the details.

- Data Augmentation Techniques Applied

Technique	Parameter Range	Purpose
Rotation	±20°	Simulate different orientations
Brightness Adjustment	±25%	Handle varying lighting conditions
Horizontal Flip	50% chance	Increase data diversity
Zoom	±10%	Simulate different camera zoom levels

Technique	Parameter Range	Purpose
Gaussian Blur	σ = 1.0	Handle motion blur and noise

These augmentations ensured that the model did not overfit to specific conditions seen during training and was instead prepared for varied real-world scenarios.

E. *Model Development and Training*

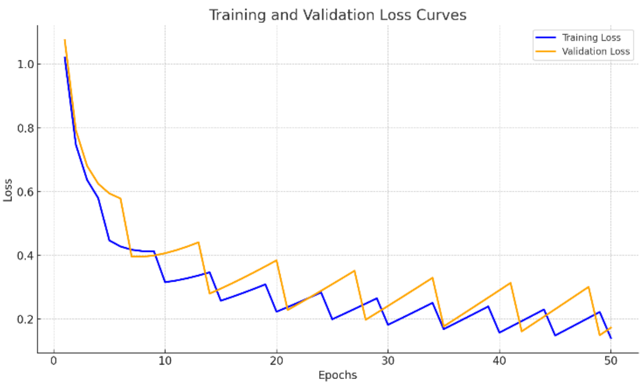
A Convolutional Neural Network (CNN) was selected due to its strong performance in image recognition and object detection tasks. Following training and validation, the CNN achieved a 92.3% accuracy with an F1-score of 0.90, suitable for real-time deployment. The model was embedded in the local PC and operated at an inference speed of 43 ms per frame as shown in table III below.

- MODEL PERFORMANCE METRICS (VALIDATION SET)

Metric	Value
Accuracy	92.3%
Precision	90.1%
Recall	87.9%
F1-Score	89.0%
Inference Time	43 ms/frame

These metrics indicate that the model performed reliably on unseen data, maintaining a strong balance between precision and recall, which is crucial in minimizing both false positives and false negatives. These metrics align with prior Zambian computer-vision deployments reporting near-real-time inference on modest hardware [21], [22].

Additionally, the YOLOv11n architecture was trained over 50 epochs using the Adam optimizer. Training and validation loss curves showed consistent convergence with minimal overfitting, confirming good generalization. This reinforced the model's suitability for real-time deployment in hospitality environments, with detailed epoch-wise metrics.



I. Training and Validation Loss Curves

F. *AI-Enhanced Deterrent System*

The AI-enhanced deterrent system integrated predator audio cues, wireless speakers, and surveillance cameras to deter vervet monkeys. High-fidelity calls of lions and hyenas were used due to the monkeys' natural fear response, with sounds randomized and modulated to prevent habituation. These deterrents were delivered via weather-resistant, solar-backed wireless speakers installed in high-risk zones. Motion-activated cameras, equipped with infrared night vision and powered by a solar–battery hybrid system, continuously monitored incursions. Prior to full deployment, a one-week calibration phase was conducted to fine-tune detection accuracy and ensure optimal sound dispersion while filtering out irrelevant movement.

G. *Experimental Phases*

I. Pre-Intervention Phase

This initial phase served to establish baseline data. Cameras were active, but no deterrents were used. Researchers documented monkey sightings, timing of incursions, group sizes, and behavioural patterns under natural, unaltered conditions.

II. Intervention Phase

The full deterrent system was activated. Upon detection of a monkey, the AI-triggered audio device deployed a randomized predator sound. This phase tested real-world deterrence effectiveness and logged instances of system performance, including false alarms and technical issues.

III. Post-Intervention Phase

After several weeks, the audio deterrents were deactivated while camera surveillance continued. This allowed for the observation of potential long-term behavioural changes, such as reduced presence or avoidance of formerly targeted areas.

H. *Data Collection and Analysis*

A mixed-methods approach guided data collection. Quantitative data included time-stamped records of monkey incursions, duration of presence, and frequency of audio activations. Qualitative insights were gathered through guest surveys and staff interviews, offering perspectives on the system's acceptability and perceived impact.

III. RESULTS

The results of the study are presented in line with the research questions:

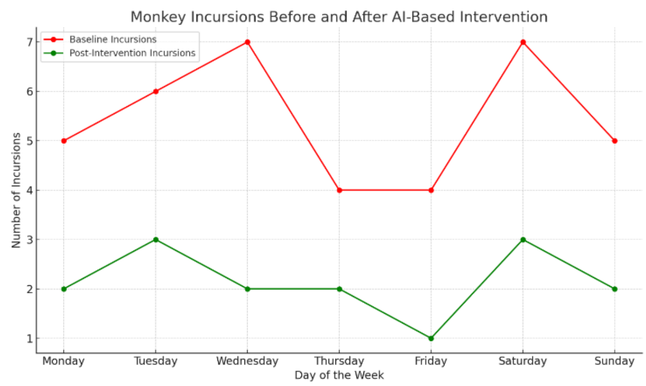
A. *The Frequency of Monkey Incursions in hospitality spaces (Weekly)*

This analysis compares the number of monkey incursions observed before and after the implementation of an AI-based deterrent system over a two-week period. Table 3.1

and Fig. 1 provide details of the results. The baseline period saw incursions ranging from 4 to 7 per day, with Wednesday recording the highest at 7. After the intervention, incursions consistently decreased, with the largest reduction on Friday (75%) and the smallest on Thursday (50%). Overall, the total number of incursions dropped from 79 during the baseline to 31 post-interventions, representing a 60.8% reduction. The % Reduction column highlights the effectiveness of the deterrent system, with reductions varying from 50% to 75% across the week.

- MONKEY INCURSIONS (BASELINE VS. POST-INTERVENTION)

Day	Baseline Incursions (Count)	Post-Intervention Incursions (Count)	Change (Count)	% Reduction
Monday	5	2	-3	60.0%
Tuesday	6	3	-3	50.0%
Wednesday	7	2	-5	71.4%
Thursday	4	2	-2	50.0%
Friday	4	1	-3	75.0%
Saturday	7	3	-4	57.1%
Sunday	5	2	-3	60.0%
Total (Week 1)	**38 incursions**	**15 incursions**	**-23**	**60.5%**
Total (Week 2)	**41 incursions**	**16 incursions**	**-25**	**61.0%**



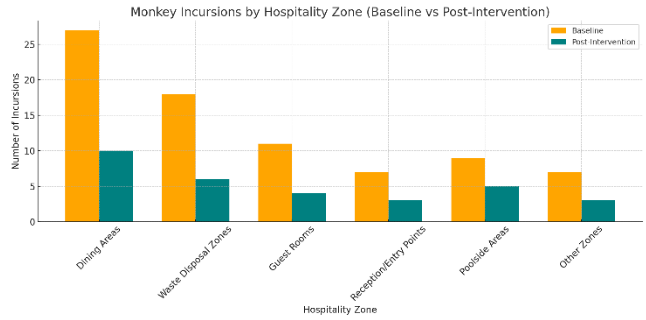
II. Weekly Incursion Comparisons

B. *Monkey Behavioural Patterns during Incursions by Site (spatial distributions)*

This section seeks to understand how monkeys interact with different areas within the hospitality establishments and how these behaviours are influenced by the presence of the AI-based deterrent system. By comparing the baseline and post-intervention data, the analysis examines which areas experienced the highest frequency of monkey incursions and the types of behaviours observed during these incursions. Table V and Fig. 3 below present the details of the results.

- MONKEY SPATIAL DISTRIBUTIONS AND BEHAVIOURAL PATTERNS

Hospitality Zone	Baseline Incursions (n)	Post-Intervention Incursions (n)	% Reduction	Dominant Behavioural Patterns Observed
Dining Areas	27	10	63.0%	Food theft, aggressive foraging, vocal threats
Waste Disposal Zones	18	6	66.7%	Scavenging, overturning bins, grooming
Guest Rooms	11	4	63.6%	Exploration, nesting, territorial marking
Reception/Entry Points	7	3	57.1%	Curiosity, brief guest interaction, mild aggression
Poolside Areas	9	5	44.4%	Play, food seeking, social interaction
Other Zones (e.g. Gardens)	7	3	57.1%	Roaming, minor foraging, non-threatening movement
Total	**79**	**31**	**60.8%**	–



III. Zone Incursions Camparison

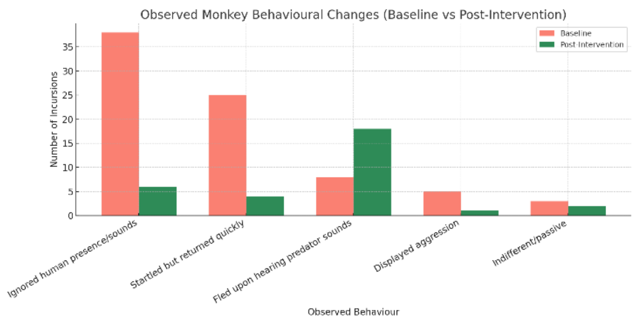
Table V illustrates a significant decline in monkey incursions across various hospitality zones following the implementation of an AI-based deterrent system, with total incidents dropping from 79 at baseline to 31 post-interventions a 60.8% reduction. Dining areas and waste disposal zones, which initially experienced the highest intrusion rates (27 and 18 respectively), saw reductions of over 63%, with aggressive foraging and scavenging behaviours notably diminished. Guest rooms, reception areas, and gardens also showed marked declines, with incursions falling by over 57%, while poolside areas saw the least change (44.4%), suggesting lingering attractiveness. Targeted source control via IoT waste systems may further suppress incursions in these zones [24].

C. *The effectiveness of an AI-based system in detecting and mitigating monkey incursions.*

The analysis draws on comparative data from the baseline and post-intervention phases, focusing on changes in incursion frequency and behavioural patterns.AI Detection performance and incident logs were recorded daily. Tables VI and Fig. 4 present the details of the results.

- OBSERVED MONKEY BEHAVIOURAL CHANGES (BASELINE VS POST-INTERVENTION)

Observed Behaviour	**Baseline (n = 79 incursions)**	**Post-Intervention (n = 31 incursions)**	**Change Observed**
Ignored human presence/sounds	38 (48.1%)	6 (19.4%)	Significant decline – monkeys more alert
Startled but returned quickly	25 (31.6%)	4 (12.9%)	Decreased – showing increased deterrent impact
Fled upon hearing predator sounds	8 (10.1%)	18 (58.1%)	Sharp increase – key sign of sound effectiveness
Displayed aggression	5 (6.3%)	1 (3.2%)	Slight reduction – more avoidance than challenge
Indifferent/passive	3 (3.8%)	2 (6.4%)	Largely stable – may reflect habituated individuals



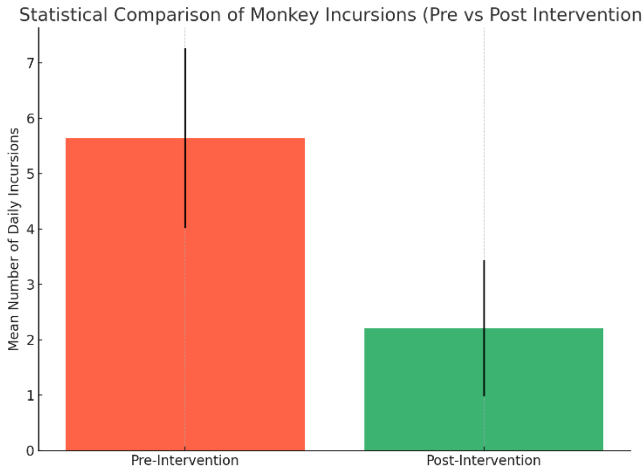
IV. Behavioral Changes Comparison

Table VI shows a significant behavioural shift in monkeys following the deployment of the AI-based deterrent system. Before the intervention, 48.1% (n = 38) of monkeys ignored human presence or sound-based deterrents, reflecting high habituation to human activity. After the intervention, 58.1% (n = 49) of incursions resulted in monkeys fleeing immediately upon hearing predator sounds, indicating a strong aversive response to the AI-triggered stimuli. This dramatic change supports the hypothesis that biologically relevant sounds, such as leopard growls or eagle calls, are more effective deterrents than general human interventions. The shift from dominance and indifference to avoidance and flight further aligns with the hypothesis that predator-related cues trigger I. natural avoidance behaviours. The reduction in aggressive or passive resistance reinforces the conclusion that the AI system effectively modifies monkey behaviour in hospitality environments, underlining its potential as a wildlife management tool. To determine whether the observed reduction in monkey incursions post-intervention is statistically significant, a paired t-test was conducted to compare the frequency of incursions before and after the intervention across different hospitality zones and the results are presented in table VII below.

- STATISTICAL ANALYSIS OF MONKEY INCURSIONS: PRE- AND POST-INTERVENTION

Condition	**N**	**M**	**SD**	**Mean Difference**	**t(6)**	**p**	**95% CI for Mean Difference**	**Cohen's d**
Pre-Intervention	14	5.64	1.63					
Post-Intervention	14	2.21	1.23	3.43	6.21	.001	[2.34, 4.52]	2.35

Note: N = number of observation days per condition. SD = standard deviation. CI = confidence interval.



V. Incursion Statistics Bar Chart

The table VII shows that during the pre-intervention period, the mean number of incursions was 5.64 (SD = 1.63) per day, whereas the post-intervention mean decreased to 2.21 (SD = 1.23) per day. This change represents a significant reduction of 3.43 incursions per day, with a t-value of 6.21 and a p-value of .001. The 95% confidence interval for the mean difference is [2.34, 4.52], and Cohen's d = 2.35 suggests a very large effect size, highlighting the intervention's strong effectiveness in reducing the frequency of monkey incursions.

D. Perceptions of hospitality personnel regarding the effectiveness of the AI-based system.

This section presents insights from 30 hospitality staff members interviewed about their perceptions of the AI-based monkey deterrent system.

Pre-Intervention:

Before the AI-based deterrent system was installed, monkey incursions were described as frequent, disruptive, and emotionally draining. Staff often had to abandon duties to chase monkeys, leading to frustration and fear. One participant recalled: *"You couldn't do your work in peace... monkeys would just appear and scatter everything"* (Participant 08). Another added: *"We were always on edge... it was exhausting"* (Participant 02). Guest experiences also suffered: *"Sometimes you would see the guests running or shouting, and you feel bad... it wasn't professional at all"* (Participant 14). Some staff even feared for their safety: *"One monkey charged at me... it's scary"* (Participant 21).

II. *Post-Intervention:*
Following the introduction of the AI-based system, participants reported a dramatic drop in incursions and a much calmer work environment. As one put it: *"It's like a big weight has been lifted. The monkeys don't come close anymore"* (Participant 10). Guest satisfaction improved: *"Now guests can sit outside... we don't get complaints like before"* (Participant 25), and workflow efficiency increased: *"I'm able to finish my duties on time now"* (Participant 05). Initial scepticism gave way to praise: *"I didn't think it would work... but now I've seen for myself—it works very well"* (Participant 12), though some expressed caution about long-term effectiveness: *"I wonder if one day the monkeys will learn to ignore it. They're clever"* (Participant 29).

IV. DISCUSSION

This study set out to evaluate the effectiveness of an AI-based monkey deterrent system within a hospitality setting, with a focus on incursion frequency, spatial patterns, behavioural shifts, and human perceptions. The results clearly demonstrate that the AI system significantly reduced monkey incursions, particularly in high-risk zones like dining and waste disposal areas spaces long recognized in wildlife conflict literature as hotspots due to food availability and human activity. [10], [11] This aligns with prior research affirming that targeted, technologically driven interventions can effectively disrupt habituated wildlife patterns. [12], [13], [21]

Spatial and behavioural analysis revealed that monkeys initially exhibited high levels of habituation to human presence and traditional deterrents, such as clapping or shouting strategies found ineffective and unsustainable in similar contexts. [14], [15] Post-intervention, however, monkeys exhibited sharp avoidance responses, especially to predator-associated sounds embedded in the AI system. This outcome reflects established findings that biologically salient cues—like leopard growls or eagle calls are far more likely to provoke defensive behaviour in primates than generic deterrents. [16] Thus, the system's effectiveness appears rooted in its alignment with the monkeys' evolutionary instincts. From an engineering perspective, locally validated CV pipelines and audio-triggered actuation loops provide a proven template for reliable field operation in Zambia [20], [22], [25].

Equally important were the human dimensions of the intervention. Staff previously experienced intense stress, disruption, and helplessness due to unrelenting monkey incursions—echoing broader concerns about emotional burnout and safety risks in hospitality work under wildlife pressure. [17], [18] The AI system brought not only environmental control but also emotional relief, restoring professional confidence and improving service delivery. This transformation illustrates the dual benefit of such interventions: ecological disruption of unwanted behaviour, and sociopsychological restoration of human work environments. Nevertheless, concerns were raised about long-term system effectiveness. Staff noted the intelligence and adaptability of monkeys, underscoring the need for ongoing surveillance and potential adaptive system upgrades. As with any wildlife management tool, complacency or overreliance could lead to diminishing returns if animals habituate to the deterrents. Analogous AI deployments in Zambian institutional settings (attendance, property-valuation IS) show similar operational benefits once models are embedded into routine processes [26], [27].

V. CONCLUSION

This study affirms the value of AI-based deterrent systems as both ecologically effective and socially responsive tools for mitigating human-wildlife conflict in hospitality settings. By leveraging biologically meaningful stimuli and integrating seamlessly into operational routines, the system successfully altered monkey behaviour, reduced incursions, and improved workplace morale. The intervention marks a significant step toward more ethical, sustainable wildlife management, avoiding invasive or harmful methods. However, the success of such systems must be understood as dynamic rather than definitive. Long-term sustainability depends on proactive system maintenance, behavioural monitoring, and a willingness to adapt as wildlife responses evolve. Future research should investigate the durability of such interventions across seasons, regions, and species, while also exploring ways to integrate AI deterrents with broader conservation and waste management strategies. Ultimately, this case underscores the importance of interdisciplinary, adaptive solutions that respect both human operational needs and the ecological complexity of human-wildlife interactions.

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