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Protecting Ancient Sites with AI Predictive Risk Modelling: What Can Be Learned from Poaching Prevention?

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ABSTRACT: In the interest of improving the field of cultural heritage conservation, it is essential to mitigate the widespread issue of looting. To apply a proper method in solving this issue, comparing solutions from other fields becomes effective. This paper surveys the latest developments in AI predictive risk modelling that have been used to prevent the poaching of endangered animals and how these models can be adapted to inform decisions on categorizing risk and allocating resources in archaeological heritage management. Heritage risk assessments have traditionally relied on expert analysis and judgment to predict risk and allocation of resources, which has created bias, blind spots, and scalability challenges. This paper presents a recommendation on how AI predictive risk modelling could be used to address these shortcomings for use in the field of heritage management. The weaknesses of the models in the context of wildlife conservation are also critically discussed to inform decision-making around the application of the models to heritage conservation and looting specifically.
KEYWORDS: Archaeology, Heritage Management, Conservation, Predictive Risk Modelling, Looting.

Introduction

While there have been many recent advancements in artificial intelligence-based predictive risk modelling, the application of these models to issues such as damage, looting, and trade in cultural artifacts has not yet been applied in archaeological heritage management.[1,2] One field where models have been applied successfully is wildlife conservation, where groups have invested in the development of predictive risk models based on artificial intelligence to improve the effectiveness of anti-poaching patrols.[1] Fundamentally, the growing record of success in wildlife conservation has not been replicated in heritage management; no comprehensive framework exists yet for adapting predictive risk modelling to the prevention of looting. However, the prevention of poaching and looting shares many challenges: remote locations that are often difficult to access, insufficient resources to constantly monitor and protect everything that needs protection, and the difficulty of identifying and tracking both the targets of the crime and the perpetrators. Wildlife protection attracts more funding and attention internationally than archaeological heritage conservation. However, this paper argues that the latest advances in predictive risk modelling for the prevention of poaching can also be used to effectively counter looting.

Helaine Silverman and D. Fairchild Ruggles of the University of Illinois at Urbana-Champaign argue that the destruction or removal of archaeological remains is an assault on "human lives and political autonomy, the cultural history and values of a community," which destroys not only cultural expressions but "the very fabric of society."[3] In addition to the cultural cost, the "black market of the antiquities trade" is conservatively estimated to be valued at $2.5 billion a year.[4] The true value of the black market fed by looting is impossible to calculate due to the circulation and storage of looted artifacts, which has occurred over centuries. As an illustrative example, it is estimated that tens of billions of dollars worth of artifacts looted by the Nazi regime during the 1930s and early 1940s are still in circulation on the black market.[5] In more recent history, the scale of looting that occurred during the Iraq War and in its immediate aftermath (2003-2017) has been described as "staggering" by the University of Sydney, even compared to the destruction and looting that "has been a by-product of war for thousands of years."[6] The looting that occurred during the instability in the Middle East through the early 21st century has contributed to a rapid increase in the scale of the black market in looted artifacts on sites such as Amazon or Facebook, with an article by Georgi Kantchev of The Wall Street Journal suggesting that over 100,000 looted artifacts are listed for sale every day online.[7] The scale of the black market in looted artifacts, however, is estimated to be smaller than the scale of the black market associated with poaching, which Interpol values at $20 billion a year.[8] However, both markets have become "a major area of activity for organized crime groups and are increasingly linked with armed violence, corruption, and other forms of organized crime."[9]

One major challenge in addressing the trade in looted artifacts—which could be rectified by preventing looting in the first place—is the difficulty of identifying them, especially distinguishing them from forgeries.[10] The challenge of identifying an artifact is increased by the lack of archaeological contextual records when an object is looted or damaged in the process of being removed from its original site. The importance of recording the context of an artifact when it is found cannot be understated: "It is said that without archaeological context all information relating to an excavated object is lost, regardless of its artistic merit."[11] In this way, the prevention of looting is similar to the prevention of poaching. Once wildlife is killed or destroyed, or an artifact is looted, the recovery of the objects

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that have been stolen offers much less value from the perspective of conservationists. Value is irreplaceably lost if an act of poaching or looting succeeds in the first instance. Therefore, it is equally vital to establish preventative measures to reduce the initial act of poaching and looting.

The field of poaching prevention has motivated technological innovations that can now be utilized in the field of archaeology to prevent looting. Given the larger scale, value, and attention given to the black market associated with poaching, significant resources have been used to develop strategies and technologies that can help prevent the initial act of poaching. Recently, focus has intensified on the development of predictive risk models, which have been refined and become more sophisticated with the application of artificial intelligence.[12] According to veteran of the technology industry Umair Khalid, in the context of poaching, a predictive risk model combines "historical incident data, geographical information, and behavioral patterns to spot high-risk areas and optimal patrol routes" for conservation rangers.[13] Khalid further explains how these models have been highly effective, with some areas seeing a 90% drop in "poaching incidents."[14]

The effectiveness of the models in conservation may be explained by how they address the weaknesses associated with reliance on human expertise for analysis and predictions. Specifically, expert assessments and forecasts on looting risk and allocation of resources in heritage management have faced challenges such as cognitive and confirmation bias, scarcity of specialists, inconsistency, and path dependence on previously identified hotspots. The assessment of sites by experts and the application of advice is often associated with what has been described as "conflicting perceptions of values."[15] The values that inform assessments and predictions can mean that some sites are allocated resources and protection that is not based on an objective assessment, which could be applied evenly to all sites requiring such protection and resources. Exacerbating this issue is the lack of domain specialists, which means certain individuals have excessive influence.[16] Without a wide range of expert views to inform approaches to practices at specific sites, the unintended biases of niche experts can lead to suboptimal assessments, forecasts, and approaches. Given the unique characteristics of individual sites and expert approaches, knowledge is also often not reproducible at different times or at different sites. For example, the reasoning behind resource allocation at a site to protect it from looting may rely entirely on an expert's background and views. Once that opinion has been established, it can lead to path dependence, with areas initially given extensive focus made more salient and seemingly important. As decisions on how to prioritize effort and resources accumulate over time, the errors created by bias, scarcity of competing specialist voices, and path dependence accumulate. It is therefore possible to see how some sites of high value still lack attention and protection, while others may receive a disproportionate level of resources.[17]

Although artificial intelligence models may, to some extent, include human weaknesses such as biases and existing path dependencies, as they are trained on data produced by humans, the development of standardized methods for assessment and forecasting with AI models could significantly reduce the influence of human error. As expert knowledge and approaches are filtered through AI models, sites that may otherwise have received a lack of attention can be revealed. In this way, the use of AI models could, over time, democratize and standardize heritage management approaches to assessment and forecasting of looting.

Given the similarities between the challenges of preventing poaching and looting, the importance of stopping the act in the first instance, and the benefits associated with reducing both crimes – including protection of cultural expression and addressing the threats of organized crime – it can be inferred that the effectiveness of the predictive risk models in poaching can inspire a similar approach and success in the context of heritage conservation management and looting. This paper uses a review of literature describing the predictive risk models that have been effective in the context of poaching and makes suggestions about how such models could be adapted to prevent looting of artifacts and areas for further research, such as how the models could be used to prevent not only looting but also the trade in looted artifacts.

Results and Discussion

Predictive Risk Modelling in the Context of Poaching: Strengths:

Use of predictive risk modelling in poaching prevention provides helpful insights into the practical strengths of the technology, which can be extrapolated to use in looting prevention. Predictive poaching prevention aims to "harness the power of data analytics, artificial intelligence, and technological advancements to anticipate and pre-empt poaching events before they occur."[18] Before the recent emergence of sophisticated artificial intelligence, conservationists used approaches such as simple occupancy models, which involved installing rudimentary networks of cameras across wide areas to identify how often poachers "occupied" a specific location. The characteristics of the locations with the highest level of occupancy were then analyzed by a computer to identify patterns that could be generalized. This approach was used, for example, in "Atlantic Forest biodiversity hotspots in Brazil" to find that higher occupancy levels of poachers were associated with proximity to "water resources, forest edges and human settlements, in areas with higher abundancy of game species, and in periods of higher lunar light intensity."[19] The success of the models was shown in various conservation contexts. For example, field tests of early machine learning models like the occupancy models showed that rangers found significantly more poaching snares on patrols when guided by insights from the models than when they relied on their own experience and judgment.[20]

Despite the continued need for expert human input and refinement, advances in machine learning and deep learning have shown high levels of success in various applications of predictive risk modelling. For example, in machine learning, a technique known as random forest—or decision making through functions of decision tree models that are trained on vast amounts of data—is highly effective at predicting and

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tracking populations of animals.[21] This approach could be used in risk models for looting by tracking movement of human populations, socio-political events, levels of poverty and unemployment, and even factors such as the vulnerability of a site based on its level of security and surrounding geographical features. Advances in deep learning have facilitated further progress that can handle aspects of image processing, such as "changes in illumination, viewpoint, and scene context."[22] However, despite deep learning advances, the scale of data input and training required is beyond the financial resources of most conservation organizations, and the decision-making processes involved in deep learning are a "black box," which refers to something AI produces that is too complex for the average human user to understand. Vishal Shah of New York University explains this type of information as "not interpretable and cannot always be validated due to their 'black box' nature."[23] A combined application of machine learning and deep learning advances would be the most effective approach to developing successful risk models in heritage management, as seen in wildlife conservation, but resource and technical limitations may dictate how, where, and when the advances can be applied. Cooperation between local and international organizations to avoid overlapping development, effective resource allocation, and sharing of capabilities will be required. However, if these obstacles are overcome, efforts to prevent looting will benefit from the advances in technology in the same way wildlife conservation has.

For example, machine learning was used to analyze the intensity of bird song to identify when populations of specific species of birds were being reduced due to poaching.[24] Artificial intelligence has also been used to address the issue of identification, with large numbers of images passed through computer vision systems to differentiate species at high risk of poaching from species that are not endangered, and also to track behaviors that could increase vulnerability to poaching.[25] Data from satellite imagery has also been analyzed with artificial intelligence to identify poaching hotspots, with this approach assessed as less disruptive than intrusive methods such as the installation of camera networks in sensitive ecosystems.[26]

Rangers in the field face a significant challenge in differentiating between poachers, legal hunters, and local people. Unless poachers are caught in the act or handling illegal goods, it is difficult to detain and charge them with any crime. However, artificial intelligence models known as Support Vector Machines (SVMs) have recently been used with an accuracy of 93% to identify poachers based on their behaviors and patterns of activity.[27] The accuracy of this method allows efficient allocation of resources to monitor suspected poachers and gather evidence of illegal activity.

Predictive Risk Modelling in the Context of Poaching: Weaknesses:

Although predictive risk modelling, especially with the ability to process massive amounts of data provided by artificial intelligence, has created powerful new approaches to preventing poaching, any adaptation for looting also needs to be informed by the weaknesses and vulnerabilities of the models. The most controversial aspect of predictive risk models is the doubt regarding the ethics of data management. As the models are trained on historical data, "if this data reflects existing biases – for instance, over policing of certain communities or prejudiced assumptions about poaching behavior – the algorithms will inevitably perpetuate and even amplify these biases."[28] Biases that could be perpetuated by the models include mistaken perceptions of race, gender, ethnicity, social status, and essentially any other characteristic that humans have created biases around. Secondly, the reliance on algorithms creates what is described as a "black box effect." If poachers or looters are identified or tracked with predictive risk modelling, the complexity of the artificial intelligence underlying the models means that the human users interpreting the results will not fully know why those results have been produced. Although conservationists who use the models will have a general understanding of the underlying principles, when the models are applied to specific data on individuals, the amount of data and the complexity of the processing would require significant amounts of time to cross-check with the model. This means that users will have to make consequential decisions based on trust in the model's processes without cross-checking every case.[29]

In early 2025, amid the rapid development and enthusiasm surrounding the potential of artificial intelligence predictive risk models, leading researchers in the field of wildlife conservation issued warnings about the use of the technology for reducing poaching. They argued that there are still significant gaps in the literature regarding the impact of the use of the technology on ecosystems. They highlighted under-resourced regions of the world, the limited integration of the models with local efforts, lack of guidelines on data privacy and wildlife ethics in general, and "the long-term cost effectiveness of AI over traditional methods." They also emphasized the need to focus on the "low-cost, low-power AI solutions adaptable to resource-scarce regions."[30] Any application of the AI-based predictive risk modelling to heritage conservation, and specifically looting, will also need to take into account these concerns.

Compared to the use of predictive risk modelling in heritage conservation, the use of the models in wildlife conservation is advanced but still only a recent development, with the basic occupancy models emerging around 2017 and 2018. However, in the last decade, the application of the models has identified the consistent weaknesses described above. To effectively address these weaknesses, researchers have argued for a stronger reliance on the "domain experts" with regional and species-specific knowledge that can enhance and direct the power of the predictive models. Although this paper focuses on analyzing the use of predictive risk modelling in wildlife and heritage conservation, the models are being developed in a wide range of fields and the same conclusion reached by researchers in wildlife conservation – that human oversight, input, guidance, and interpretation of predictive risk models is essential – has been reached in fields as diverse as enterprise risk management and surgery.[32,33]

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Conservation Heritage: Predictive Risk and Prevention of Looting:

Although AI predictive risk modelling has yet to be applied to the prevention of looting, these types of models have been used in attempts to predict other forms of crime, especially the identification of urban crime hotspots.[34] However, the models created to address these crimes would fail to accurately address the issue of looting due to the characteristics that looting shares with poaching as described above: often remote locations with difficult access and a lack of resources to monitor the vast number of artifacts vulnerable to looting across large areas of geographic space.

The characteristics that differentiate the use of AI predictive risk modelling in heritage management from general crime can be seen in the limited number of research papers that have emerged since 2020 that explore the possible application of the models to looting. Research arguing for the integration of data from Geographic Information Systems (GIS) to inform AI predictive risk modelling for the prevention of looting identifies factors such as "elevation, proximity to water sources, soil types, and historical land use" as significant for creating accurate models in this context.[35] The overlap of these factors with some of the factors identified in the application of the models to wildlife preservation can be seen, while the lack of overlap with factors that might inform general crime models is also clear.

Although professionals in heritage management have used large-scale data analysis systems like GIS for mapping and recording extensively, AI predictive risk models have had limited use within the field. For example, one recent study looked at the use of risk models with LiDAR (light detection and ranging) data to assess the condition of submerged archaeological sites at reservoirs and predict risks associated with erosion.[36] Similarly to the early uses of large-scale data models in wildlife conservation, conservationists in heritage management first started to use data from camera networks and satellite imagery from around 2016.[37] However, the large amount of data gathered from this approach required "time-consuming direct interpretation of images, with the potential for human-induced error."[38] The analysis of satellite, camera feeds, and open source data—such as Google Earth—for the identification of at-risk sites and the prevention of looting was described as "expensive, time-intensive, difficult to replicate, and gappy."[39] Another study that explored the feasibility of using artificial intelligence monitoring to assess the effects of climate change and air quality on heritage sites concluded that constant monitoring and assessment of sites with artificial intelligence was possible and cost-effective.[40] The emergence of high-performance artificial intelligence should have reduced the impact of some of these issues with the approach, and some attempts have been made to apply AI predictive risk models to prevent looting.

In 2023, research was published on the use of deep learning models and optical unmanned aerial vehicles to identify looting at heritage sites.[41] However, the research focused only on the identification of looting once it had occurred, not on its prevention. In 2024, a European project called SIGNIFICANCE was created to use artificial intelligence and deep learning to enable "authorities to identify, track, and block illegal activities in the online domain, thereby aiding successful prosecutions of criminal networks."[42] The early results from SIGNIFICANCE show a "10-15% increase in the identification of illicit artifacts" online.[43] Despite these examples of the potential for advances in artificial intelligence to be applied to heritage conservation, the prevention of looting with real-time predictive risk models has not yet been fully developed, as it has in wildlife conservation.

By imitating the approach taken in wildlife conservation, conservationists in heritage management could create predictive risk models that inform decision-making on resource allocation to prevent looting. For example, as shown above in wildlife conservation, rangers are guided by insights from predictive risk modelling that not only identify sites where poaching is likely to happen but also help identify the poachers in real time. Although there is significant overlap between the characteristics of the goals and challenges of wildlife and heritage conservation, the lessons of wildlife conservation need to be adapted to the heritage conservation context.

Towards a Real-Time Predictive Risk Model and Identification of Looters:

Based on the developments and lessons of the artificial intelligence predictive risk models in wildlife conservation, conservationists in heritage management should focus on three main areas: the identification of effective technologies for data collection necessary for the risk models in the context of preventing poaching, using expert insight to continuously refine the risk models and ensure alignment with heritage management priorities, and establishing effective physical enforcement procedures and policies to be applied at sites identified as vulnerable to poaching that have been prioritized by the risk models. In the long term, heritage management professionals could also explore the use of robotic or automated deterrence measures at heritage sites to stop looting. Figure 1 provides a broad comparative overview of the objectives, inputs, outputs, and human feedback used for wildlife conservation and those that could be used in heritage management as predictive risk models for the prevention of looting.

As shown in Figure 1, the objectives of AI predictive modelling share the requirement for identifying at-risk objects and ranking them by risk, and a comparative evaluation of the potential effectiveness of resource allocation. Both fields require real-time feedback to be as effective as possible. However, wildlife conservation requires systems that can identify and track moving animals, whereas heritage management predictive risk models will mostly be focused on static sites. There could be some elements of tracking movement in heritage management systems, such as proximity and movement of identified potential looters or vulnerable populations fleeing conflict, but the challenges of tracking the movement of wildlife populations do not have an equivalent in heritage management. Recent attempts to use aerial and satellite imaging show the fundamental difference in temporal resolution when monitoring potential looting activity compared to wildlife protection.

For monitoring the emergence of exploratory pits for looting, yearly, quinquennially, and monthly temporal resolutions have been effective.[44] For the prevention of poaching, such temporal resolution is ineffective. The difference can be seen in the inputs, where species movement and density do not correlate with heritage management, but the similarities between inputs, such as historical incident data and socio-political data, show how the successful application of such inputs in wildlife conservation could be transferable to heritage management.

The outputs required for both fields are defined by dynamic, real-time updates and feedback loops with suggestions for resource allocation to guide expert decision making. Figure 1 provides an overview of the similarities and differences between the processes and requirements in wildlife conservation and heritage management. For effective predictive risk modelling, the outputs require expert assessment in both fields, which can be used to refine the objectives, the collection of input data, and the processing of that data.

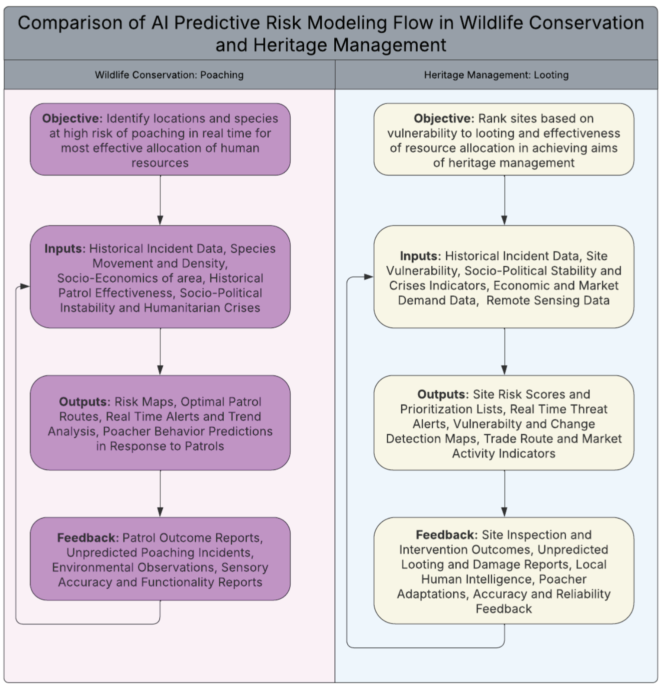

Figure 1: This shows a comparison of AI predictive risk modelling flow in wildlife conservation and heritage management, including the differences and similarities between objectives, inputs, outputs, and feedback.

Although large-scale data models, deep learning, and artificial intelligence models have been used in various ways in heritage management, as described above, there has been no attempt yet to use predictive risk models to inform decision-making and procedures that could stop looting before it occurs or in its early stages. The high cost of rapid reaction to the appearance of potential looters at a site means that 24/7 human monitoring is often impractical or unfeasible. In contrast, artificial intelligence predictive risk models that have been trained to align with conservationists' priorities could identify potential cases of looting before they happen or in their early stages. To date, efforts to address looting have largely focused on identifying already looted artifacts, but the decontextualization of artifacts as a result of looting leads to the irreversible loss of valuable information about the artifact itself and the site in which it was found.

Although this paper explores the general potential for predictive risk models in the prevention of looting, their application in the context of wildlife conservation shows that expert shaping of the systems is necessary to create the most value. For example, the tracking of bird song intensity to identify populations suffering from poaching could be replicated in the context of preventing looting with creative applications such as the analysis of excavations or activity around a vulnerable site with artificial intelligence to identify patterns associated with looting behavior.

The creation of real-time artificial intelligence predictive risk modelling for looting poses significant challenges. However, the use of similar models in wildlife conservation suggests that it is possible to use these models to prevent looting.

Specific Technologies to Be Adopted:

Unmanned Aerial Vehicles (UAVs) have the potential to revolutionize real-time looting risk analysis with the aim of informing effective resource allocation for prevention. Latest developments in the specific technologies being adapted for UAVs and that could be used in heritage management include, but are not limited to, a wide range of cameras such as thermal, red green blue, and monochrome; light detection and ranging (LIDAR), which creates 3D maps of the target environment;[45] and RADAR to detect and track almost any object "in the air and on the ground."[46] Advanced object detection methods are also in development, which combine with AI analysis of curated data sets to rapidly provide feedback to predictive risk models. Examples of such data sets available to these types of models in heritage management include but are not limited to: Common Objects in Context (COCO), which is one of the most widely used datasets for object detection;[47] KITTI Vision Benchmark Suite, which includes LIDAR, GPS, and various sensor data mainly for the development of autonomous driving but would also be useful for "object detection, tracking, and classification" at sites that face a high risk of looting;[48] Sentinal-2, a European satellite program that provides "high-resolution multispectral imagery of the Earth's surface" and has "been widely used for land cover mapping, change detection, and vegetation analysis,"[49] all of which would be useful for analysis of sites at risk of looting; and DigitalGlobe, which commercially offers "high resolution satellite imagery with a spatial resolution of up to 30cm."[50]

One major concern with predictive risk models is missing data. In the context of heritage management and the prevention of looting, missing data could include anything from human error leading to missed functionality issues with sensors to out-of-date location data for specific objects at a site at risk of looting. However, Multiple Imputation with Chained Equations (MICE) technology has been developed to facilitate statistical analysis of datasets that create a range of most-likely inputs, which can be used when data is missing.[51] The MICE technology provides stable parameter estimates even when there is a lot of missing data, and it maintains computational scalability. This method can effectively reduce overconfidence

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in any uncertain data in the prevention of looting, thereby mitigating any problems that could arise from missing data or human error.

Finally, the use of new technologies such as UAVs, cameras, sensors, datasets, and statistical models to address missing data can be combined as an Internet of Things (IoT) approach to looting prevention. This approach has recently been adopted for "monitoring, predictive maintenance, and decision making" for "protecting cultural heritage buildings."[52] The use of the IoT approach to the prevention of looting will require the adoption of the technologies described above and the prioritizing of identifying new technologies that can be adapted to this field as they emerge. Figure 2 shows a proposed workflow process for the integration of predictive risk modelling in the prevention of looting.

The data collection stage shows the integration of human expert knowledge and analysis, and the collection of raw data, through precision equipment. Although the data collected can be accumulated as and when available, without prioritization, it may be discovered that the model is more effective when one or more elements of data collection are prioritized. The stage of deep learning processes most likely requires strict ordering, as each stage will require the completion of the previous stage. Object identification will be required first, followed by the filtering of irrelevant data. For example, an increase in demand for a certain type of artifact online would require an identification stage to match the artifact with sites at risk of looting. Such an identification process will require a stage of filtering to ensure mistaken identification does not influence the risk assessment. The risk assessment will be highly complex and will need to be refined by the feedback loop of the entire process. The risk assessment will dynamically adapt to the refinement of expert input and advances in data collection technology and machine learning.

The ranking of risk will be as complex as the risk assessment, with the process of prioritization refined by the expert input and evaluation of the effectiveness of available resource allocation that is dependent on location and dynamic conditions. Once the deep learning processes are complete, the autonomous decision-making has effectively occurred. The third stage is making the decisions available, with reasoning, to the groups or individuals responsible for final approval. The final stage of expert analysis will provide another opportunity for the input of human values and priorities and act as a safety net to mitigate potential errors. Within these final two stages, there will be an immediate alert process for the highest priority cases where immediate action is required. The immediate alert will raise awareness of issues for experts to make a final decision on. If the emergency alerts are found to be misaligned with priorities or unnecessary, the expert decision-making at the fourth stage will be fed back into the system through the feedback loop of data collection. Figure 2 shows a summary of the stages, with a focus on how a feedback loop can be created to ensure expert human input shapes the entire process.

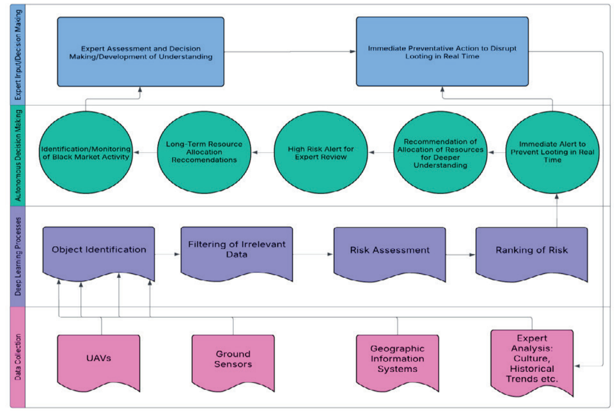

Figure 2: This visualization of the possible workflow of a predictive risk model for the prevention of looting shows four stages of data collection, the deep learning process, autonomous decision making, and a final stage of expert input and decision making. The figure shows how the stages interact and create a feedback loop to refine the process.

Ethics Considerations:

As previously mentioned, one aspect of the pervasive use of AI that requires careful consideration, especially as it is integrated into the IoT, is the ethics of data management. Subjects such as data sovereignty, potential conflicts over data collection, storage, and use with local communities and governments, and transparency and accountability mechanisms need to be considered. These subjects are being addressed in a wide range of fields, beyond wildlife conservation and heritage management. Privacy-preserving methods of data collection, storage, and usage have been developed in recent years, including "dynamic anonymization, homomorphic encryption for secure computation, and AI-driven access control systems."[53] Dynamic anonymization involves anonymizing digital data as soon as it is collected by sensors associated with the IoT. Homomorphic encryption then allows encrypted or anonymized data to be processed without first having to decrypt or deanonymize the data.[54] If data does need to be deanonymized, AI-based access control systems are in development, with AI used as a gatekeeper to ensure that only individuals with the proper authorization are able to access, use, and/or transfer such data.[55] Ethics considerations across various jurisdictions will increase the complexity of adopting predictive risk models. However, transparency, fairness, and privacy are fundamental to the effective development of technologies such as predictive risk models in heritage management. Any attempt to use the latest developments in technology should be based on transparency, fairness, and privacy to ensure support among local communities and stakeholders.[56]

Obstacles:

One significant obstacle to implementing a predictive risk model for the prevention of looting is the cost of real-time heritage site monitoring. Although sources of real-time data, such as unmanned drones, cameras, networks, and satellite imagery, are widely available and becoming cheaper to access, create, and monitor, the number of heritage sites worldwide that are vulnerable to looting and the cost associated with establishing the 24/7 monitoring required for the prevention of looting is likely to prevent the creation of a comprehensive system. However, one of the benefits of the development of a predictive risk model would be the ability to rank sites' vulnerability to looting and allocate resources more efficiently. It may not be feasible to protect all sites in real time, but the development of the model will inform decision-making regarding which sites would benefit most from such monitoring, which sites would be difficult to protect even with such monitoring, and where limited resources can be allocated for the highest level of return value. As described in the discussion of wildlife conservation, although predictive risk models can inform such decision-making, a continuous evaluation and assessment of the models' input and output by experts within the field would be required to ensure the models are aligned with the aims of conservationists and society at large. Estimates of costs will vary depending on the specifics of each site, such as scale, accessibility, climate, concurrent human activity, economic status of the region, as well as unique variables that can only be assessed by experts familiar with the site, culture, and objects being protected. However, given the conservative yearly estimate of US$2.5 billion in losses caused by looting, a comparison of some general cost estimates associated with the emerging technologies will help to put the obstacle of cost in perspective.[57] At the most abstract level, the EU's ENIGMA project, the total cost of which is estimated at approximately EUR €4 million (approx. US $4.3 million), is expected to "achieve excellence in the protection of cultural goods and artefacts from man-made threats by contributing to their identification, traceability, and provenance research, as well as by safeguarding and monitoring endangered heritage sites."[58] Costs of modular nodes that feed movement and thermal data into the IoT are falling rapidly, and recent attempts to identify nodes that can be used in heritage management protection have found that "robust performance, low power consumption, and cost-efficiency" can be achieved for "less than GB £200 (approx. US $260) per node."59 In 2026, the starting costs for a fully functioning IoT system designed for a specific use case are estimated as: US $30,000 for hardware, US $50,000 for software development, US $4-12 for connectivity fees, and US $10,000 annually for maintenance.60 The initial cost in hardware and software development far outweighs the ongoing costs of connectivity and maintenance, so coordination between regional groups to share software development when possible would increase accessibility to these new systems.

Furthermore, the ethical issues of data collection and processing at vulnerable sites, especially when attempting to predict crimes, are already causing significant controversy around the use of artificial intelligence predictive risk modelling for crime in general, and a similar level of controversy could be expected for usage in heritage management. However, as described, sites vulnerable to looting are often remote or isolated, or difficult to access for other reasons such as war or natural disaster, so the general public would be much less likely to be exposed to the models' data capture processes, such as taking, storing, and processing images, than with general crime predictive models in contexts such as urban environments. It may also be possible to make visitors of vulnerable sites aware that this type of data collection and modelling is happening, which would reduce concerns around the ethics of such systems and have the secondary benefit of acting as a deterrent for looting. This type of awareness raising could happen even at remote sites without human presence through technology such as remote cameras, drones, and microphones.

Finally, even if artificial intelligence predictive risk models are implemented at archaeological sites, a role similar to the wildlife ranger is needed to respond to the threat of looting and confront, challenge, and apprehend potential looters. With developments in remote technology, it may be possible to use automated drone systems or robotics in this role in the future, but in the immediate future, heritage conservation and the prevention of looting will likely require the employment of trained staff to fulfil a similar role to the wildlife ranger. Legal and ethical obstacles related to the use of AI prediction for the identification of potentially criminal behavior will vary between jurisdictions, but with the increasing use of these types of models across societies, their use in heritage management and the prevention of looting will likely be integrated into the developing legal frameworks.[61] However, it is important to note that in various fields where AI predictive risk modelling is being applied, there is recognition that human input is required for ethical and moral purposes, regardless of the potential effectiveness of predictive risk models.[62]

Conclusion

The black market in artifacts and the looting that fuels that market are growing rapidly and cause significant, irreversible damage to physical sites, cultures, societies, and individuals. Advances in large-scale data collection and processing have led to advances in identifying looted artifacts and sites that have been looted, but unlike in wildlife conservation, no serious attempt has been made in heritage conservation to use the developments in artificial intelligence to create predictive risk models that help to prevent looting before it happens or in its early stages, ensuring that artifacts retain their value. This paper demonstrates how the use case of wildlife conservation provides a framework that could be applied to heritage conservation to create effective predictive risk models to prevent looting. Significant obstacles and challenges exist in the development of such an approach in heritage management, but wildlife conservationists have shown that it is possible and highly effective. Table 1 shows a broad summary of tools and approaches used in wildlife conservation that can be applied to looting prevention risk modelling.

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Table 1: Table 1 provides a summary overview of the transferability of specific approaches and tools that can be used in predictive risk modeling in heritage management when transferred from wildlife protection. The summary includes descriptions of capabilities and limitations and an assessment of transferability.

Summary Overview: Transferability of Approaches and Tools

	Capabilities	*Limitations*	*Transferability*
Integration of Geographic Information Systems	• Pattern identification for assessing vulnerability of sites to looting • Informs dynamic real-time assessment of risk	• Does not take into account social, cultural, and economic factors that affect risk assessment • High cost of a comprehensive system that requires systematic updating	• Highly Transferable. • Once patterns associated with vulnerability have been established, they can be applied and updated in the same way as wildlife management
Deep Learning Models	• Identify, track, and block illegal activity related to looting online, disrupting black markets, and reducing demand • Can also be used to inform dynamic real-time assessment of the risk of looting at sites	• Input data quality determines effectiveness • Identifying bias within large datasets can be challenging • Large-scale data processing of this type risks perpetuating errors within existing datasets • Missing data can also lead to ineffective conclusions	• Highly Transferable. • Deep learning can be used to create sophisticated models for specific sites or to rank identified sites by importance. The potential uses are essentially unlimited, but most importantly include resource allocation, risk identification, and dynamic/real-time assessment
Unmanned Aerial Vehicles (UAVs)	• Constant surveillance of specific sites • Various camera options, including red, green, blue, monochrome, LIDAR, thermal	• Cost of equipment purchase and maintenance • Weather conditions can limit effectiveness	• Highly Transferable. • As sites at risk of looting are overwhelmingly static by nature, replicating the success of UAVs in wildlife conservation, with protection of animals in constant movement, should be a straightforward goal
Object Detection Datasets and Tools	• Can be integrated with various sensors and camera systems, including static and autonomous	• As with other datasets, it requires high-quality input data to be effective • Integration of datasets and tools requires high levels of expertise	• Moderately Transferable. • As sites are static, object detection is relatively simple, but in contexts such as monitoring online black-market activity, object detection will be important
Internet of Things (IoT) ** Many of the elements of IOT overlap, such as how statistical datasets and sensors combine to facilitate deep learning. This assessment takes a broad overview of the system as a whole*	• Real-time, dynamic assessment of risk of looting • Monitoring and identification of black-market activity • Tracking and prediction of looter behavior and decision-making • Reduced costs for constant surveillance and dynamic alerts to risk	• Ethical and legal considerations regarding data collection and use vary across jurisdictions and could create high levels of complexity and cost • Standardizing an approach across cultures and jurisdictions, for example, the allocation of resources at an international level, will require high levels of cooperation • Cost of creation and maintenance is high • Scarcity of expertise for creation and effective application	• Highly Transferable. • IoT will become the foundation of most systems that monitor and assess real-time activity. It will be used to inform expert decision-making in some contexts and become fully autonomous in others, reducing cost and increasing effectiveness

Limitations

The limits of this research include a lack of comparison with other fields in which predictive risk models have been used. Further research could analyze whether the application of these models in other fields contains further insight for their use in the prevention of looting. Furthermore, research is required on the costs of preventing the act of looting once high-risk situations have been identified. It may be possible to use advances in robotics and automated systems to prevent looting as the sites and artifacts are static, reducing the cost of installing fixed systems, unlike the prevention of poaching, which requires constant movement, tracking, and monitoring of wildlife patterns. It is also possible that existing uses of large data sets in heritage management, such as GIS to map sites, could contain data that can be used in developing predictive risk models for poaching, but assessing this possibility is beyond the scope of this paper.

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