Smith Institute

Spectrivity

# Artificial Intelligence for Spectrum Management

Commissioned by:
**uk spectrum** policy forum

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# Executive summary

**Artificial Intelligence (AI) stands poised to revolutionise spectrum management, offering a powerful solution to critical resource scarcity. Maximising innovation for efficient and optimal use of spectrum is a key priority of Ofcom for the UK's spectrum management. Through spectrum sharing, forecast-driven decisions, and automated interference control, AI could dramatically enhance the value realised with UK spectrum.**

The UK faces critical challenges in achieving greater efficiency in spectrum utilisation and assignment, driven by increasing demand for wireless services, and the need to maximise the socio-economic value of spectrum. Managing spectrum is a careful balance of policy, technology and stakeholder interests.

## Key Challenges

Challenges in managing spectrum that highlight the complexity of balancing competing demands whilst facilitating access to innovation include:

- Driving improved, affordable connectivity
- Monitoring for licencing and compliance
- Managing interference in shared spectrum
- Defining efficient sharing frameworks
- Unlocking efficient allocation of public subsidy with data

Commissioned by the UK Spectrum Policy Forum to conduct this study, Smith Institute and Spectrivity bring world-class expertise in the cross-sector use of AI to drive innovation and organisational efficiency, alongside first-hand UK spectrum management experience. We identify key use cases and opportunities where AI has the potential to positively impact the spectrum landscape.



## Opportunity Areas

The potential for AI in spectrum management is vast. In the following sections, we will explore a range of use cases, highlighting their possible impact, feasibility, and time to value. We consider:

**Licencing applications** to improve the efficiency and consistency in assessing the impact on incumbents when assigning new licences

- Language models for automated licence application review to increase efficiency
- Using machine learning (ML) to predict interference coupled to optimisers like Gurobi, to achieve the maximum possible coverage
- Feature extraction methods to develop meaningful utilisation and coverage metrics for AI-driven modelling

**Proactive monitoring and compliance** through data collection and exploitation best practice, for internal efficiency and proactive targeted monitoring

- Experimental design approaches for licence violations detection
- Automated design of sensor placement against interference and coverage objectives
- Anomaly detection methods for automated flagging of suspicious activity

**Spectrum sharing and interference management** to prevent and mitigate interference, providing better decision-making around spectrum sharing opportunities, which aims to unlock more spectrum availability to stakeholders

- AI for dynamic spectrum allocation, predicting and preventing interference between competing sources, and also exploiting any idle frequencies
- Machine-supported decision-making techniques for policy making and workload reduction

**AI for simulating signal propagation** using public dataset analysis to provide actionable insights into spectrum effectiveness and policy outcomes

- Coverage and signal propagation modelling to enhance spectrum utilisation
- Testing of sharing technologies to boost innovative use
- Digital twins for improved policy decisions and technology adoption

Hybrid approaches, that combine AI with conventional methods, are adopted in some current AI spectrum applications. Several AI techniques may also be combined, to obtain the optimal solution and maximum benefit to the use case.

## Innovation & Adoption

The pace of innovation in this field is rapid. Innovation in AI demands continual updating of regulatory procedures to stay current. Building trust through explainable and validated AI systems with human oversight is crucial. While comprehensive AI regulation is still emerging, the foundation rests on five key principles: safety, robustness, fairness, accountability, and contestability.[1]

To leverage AI for improved spectrum management, Ofcom and other regulators must gather and maintain quality input data, which we explore within the report. A thorough cost-benefit analysis (CBA) of proposed AI techniques is essential to evaluate their potential impact and value before implementation, for which we highlight key inputs for a CBA.

In general, training costs for AI systems are high. However, through transfer learning to fine-tune existing or open-source models, combined with generative techniques for data augmentation, this expense can be reduced. The value unlocked through AI applications increases over time as models learn from new data. Curating and maintaining quality data is crucial to improving spectrum management efficiency with AI. Strategies to frequently update systems with the latest frequency allocation, licencing, and compliance data must be developed and executed effectively to achieve the greatest benefits.

[1] Department for Science, Innovation & Technology, A pro-innovation approach to AI regulation - GOV.UK, (updated) Aug 2023.

# Contents

# 1 Introduction

**Spectrum is a finite resource. Our appetite for wireless technology seems infinite. In this tension lies a fundamental challenge for telecommunications – and artificial intelligence (AI) may hold the key to solving it. As the UK faces increasing demand for wireless connectivity, transforming the landscape of spectrum management is ever pressing.**

Wireless technology is evolving, with many competing applications, which means the demand for spectrum is increasing. Managing access to spectrum is crucial for reliable communications. However, the spectrum is already heavily subscribed, with many frequencies in high demand which can cause congestion and interference. Traditional management methods are often rigid and unable to adapt quickly to the dynamic needs of modern networks. This results in some parts of the spectrum being underutilised, while others are overburdened. The emergence of new spectrum-hungry technologies threatens to push current management approaches to their limits.

Dynamic decision-making and adaptation to real-time conditions is the bread and butter of AI. It is a tool primed for managing complex systems like spectrum allocation. AI thrives on data. Spectrum management is inherently data-rich – usage data, interference data, performance data – so it is teeming with possibilities for AI to optimise resource usage, reduce interference and enhance network performance.

Given estimates that AI could add over half a trillion pounds to the UK economy by 2035[2], the UK Government's AI Opportunities Action Plan aims to harness this new technology to enhance public services, increase productivity, and boost growth[3]. The rapid advancement of AI offers many possibilities for more efficient spectrum management, greater spectrum utilisation through data-driven policy making, and the automation of time-consuming back-office activities – all now within Ofcom's reach.

The term 'artificial intelligence' is now part of everyday conversations. This widespread familiarity can be attributed to both the pace of progress and the increasing integration of AI into aspects of daily life, from virtual assistants to search engines to social media. Many people have become particularly familiar with generative AI and large language models (LLMs) like ChatGPT by OpenAI, Google Gemini, and Claude by Anthropic. These tools can generate human-like text and assist with many tasks, making AI more accessible and useful to the general population.

In March 2024, the National Audit Office reported that 70% of the UK government bodies surveyed were piloting and planning AI use cases[4]. The Prime Minister recently announced ambitious plans to support AI innovation, to "make Britain the world leader in AI[5]." These include unlocking public data, for use in training AI systems, and establishing designated 'AI Growth Zones' with fast-tracked planning for data centres. Multibillion-pound contracts will be signed to build the public "compute" capacity, which they aim to increase by twentyfold over the next 5 years.

Artificial intelligence refers to computer systems that perform tasks which typically require human intelligence, such as reasoning, learning and decision-making. For the purposes of this study, we define AI as the ability to make intelligent decisions with data. The terms 'artificial intelligence' and 'machine learning' are often used interchangeably. Broadly speaking, AI describes the wide variety of machines exhibiting intelligence, while machine learning (ML) is a subset of AI that involves using computational algorithms to learn patterns in data and inform decision-making.

Learning meaningful and valuable patterns in data first requires clean, machine readable, and high-quality data. The availability of data also influences AI use-cases an organisation can pursue. To achieve transformative and sustained benefit from AI, organisations must acquire and maintain relevant data. We discuss options regulators have for data exploitation, which includes the opportunity to leverage public data through the National Data Library[6]. Beyond this, we highlight promising techniques to enable AI use-cases where data is sparse.

In this study, we map the global state of play in AI for spectrum management. We describe data-driven tools and algorithms that may unlock data-informed decision making for spectrum management. We identify both established and nascent AI techniques that have the potential to reimagine existing UK spectrum procedures. For these techniques, we consider practicalities of implementation and adoption. This includes assessing the viability of regulatory, operational and data requirements, as well as recommending inputs for consideration in a future cost-benefit analysis to help regulators and/or organisations assess the feasibility of implementing potential AI techniques into spectrum management.

[2]Microsoft UK Stories, AI could boost UK GDP by £550 billion by 2035, research shows, May 2024.
[3]Department for Science, Innovation and Technology, AI Opportunities Action Plan, Jan 2025.
[4]National Audit Office, Use of artificial intelligence in government - NAO report, Mar 2024.



[5]Department for Science, Innovation and Technology, Prime Minister sets out blueprint to turbocharge AI - GOV.UK, Jan 2025.
[6]ARD UK, The new UK Government wants a National Data Library..., Aug 2024.

# 2 Current spectrum management: context and challenges

**Managing spectrum is a careful balance of policy, technology, and stakeholder interests. As a finite resource, spectrum requires careful stewardship to maximise social and economic benefits, while ensuring efficient allocation across users. To explore how AI may transform spectrum management, it is key to understand the current landscape – from its governance structure through the Department for Science, Innovation and Technology (DSIT) and Ofcom, to the practical challenges of spectrum assignment, licencing, and sharing. Understanding this ecosystem – its stakeholders, processes, and challenges – provides essential context for exploring how AI can enhance and transform spectrum management practices in the coming years.**

## 2.1 Spectrum management in the UK

**The Department for Science, Innovation and Technology (DSIT) is the lead department for spectrum policy, reviewing the legal framework and setting strategic direction for UK spectrum management. DSIT's 2023 Spectrum Statement[7] defines four key management principles:**

1. Spectrum is a strategic asset and an important enabler for a range of government policy objectives.
2. Spectrum management should promote innovation and investment alongside consumer-focused outcomes.
3. Spectrum management should ensure efficient and optimum use and be linked to actual usage with users empowered to make decisions where appropriate.
4. Spectrum management should itself take best advantage of innovation as well as supporting innovation in the services which use spectrum.

[7]Department for Science, Innovation & Technology Spectrum Policy Statement 2023, Spectrum statement - GOV.UK, April 2023.



These align with DSIT's overarching aim to '*Accelerate innovation, investment and productivity through world-class science, to ensure that new and existing technologies are safely developed and deployed across the UK and drive forward a modern digital government for the benefit of its citizens*'[8]. Understanding rapid developments in AI technology and applying them across sectors clearly aligns with wider government policy.

The Office of Communications (Ofcom) is the principal body for spectrum management in the UK. It is responsible for authorising access and setting the rules for spectrum use[9]. While Ofcom manages civilian use of the radio spectrum in the UK, public sector use is typically managed by the relevant government department. Government departments – particularly The Ministry of Defence (MOD), Home Office (HO) and Department for Transport (DfT) - are major users of spectrum in the UK. Around 52% of UK spectrum is accessed by the public sector.

There is close cooperation between government users and Ofcom. Interdepartmental bodies are key for this, such as the Spectrum Board, the Public Sector Spectrum Release (PSSR) programme and the Central Management Unit (CMU). The concept of recognised spectrum access (RSA) facilitates trading in public sector spectrum[10]. Yet, challenges remain in finding an appropriate balance between the public sector's rights to use the spectrum being shared and the rights of those they share spectrum with.

Ofcom's Spectrum Roadmap (2022)[11]describes its overall vision in four themes:

- Wireless connectivity: Continued improvements in the wireless communications used by everyone, wherever and whenever they use them.
- Access to appropriate spectrum: Businesses, public sector and other organisations with specialised requirements will be able to access the right wireless communications or spectrum options for them.
- Flexibility: Increased flexibility in spectrum use to support innovation, with appropriate assurances for continued use.
- Efficiency: Sustained improvements in the efficiency of spectrum use.

The main themes of future work areas outlined in the Spectrum Roadmap are: reviewing the impact of new technology and network convergence to inform spectrum policies, supporting wireless innovation and sharing (e.g. through spectrum 'sandboxes'), and improving data that can be leveraged for spectrum management. Each of these areas offers opportunities for AI-based enhancement.

Before exploring these, it is important to understand spectrum management policies and priorities, including the roles key stakeholders and the need for efficient utilisation. In practice, this entails licencing, monitoring, sharing frameworks and many other processes. Understanding these aspects is crucial as they shape allocation and usage, impacting both national and international communication.

[8]Department for Science, Innovation & Technology, About us - Department for Science, Innovation and Technology - GOV.UK.
[9]Ofcom's powers are derived from the Communications Act (2003) Communications Act 2003: Eleventh Report on the Secretary of State's functions - GOV.UK and the Wireless Telegraphy Act (2006) Wireless Telegraphy Act 2006.
[10] Ofcom, Recognised Spectrum Access (RSA) for Receive Only Earth Stations - Ofcom, March 2015.
[11]Ofcom Spectrum Roadmap (Updated) 2022, Spectrum Roadmap: Delivering Ofcom's Spectrum Management Strategy, April 2022.

## 2.2 Policy and priorities

**UK spectrum management operates within a wider international framework governing frequency allocation among diverse stakeholders. Spectrum does not respect borders, so it is managed both within and between nations. Many decisions are made across countries through organisations like the World Radiocommunication Conference (WRC). Ofcom represents the UK in spectrum discussions at international bodies such as the ITU, CEPT and EU spectrum policy.**

In these discussions, there is a key balance between cooperation and security. In some bands, spectrum sharing is difficult by nature, for example, NATO bands are protected due to their operations. The UK is exposed to geopolitical events, so permitting sharing in such bands can create vulnerabilities. The cost of the added risk can outweigh the benefits.

### 2.2.1 Assigning spectrum

Spectrum is allocated depending on use-type in the UK Frequency Allocation Table[12], maintained by Ofcom and updated with respect to international use, based on the ITU-R WRC, which occurs every four years. Licences are granted for a certain period, from days to years or indefinite. Some licences are for near-instantaneous access through dynamic sharing frameworks. In addition to the duration (pertaining to all licences), there are three broad approaches to spectrum licencing (Figure 1).

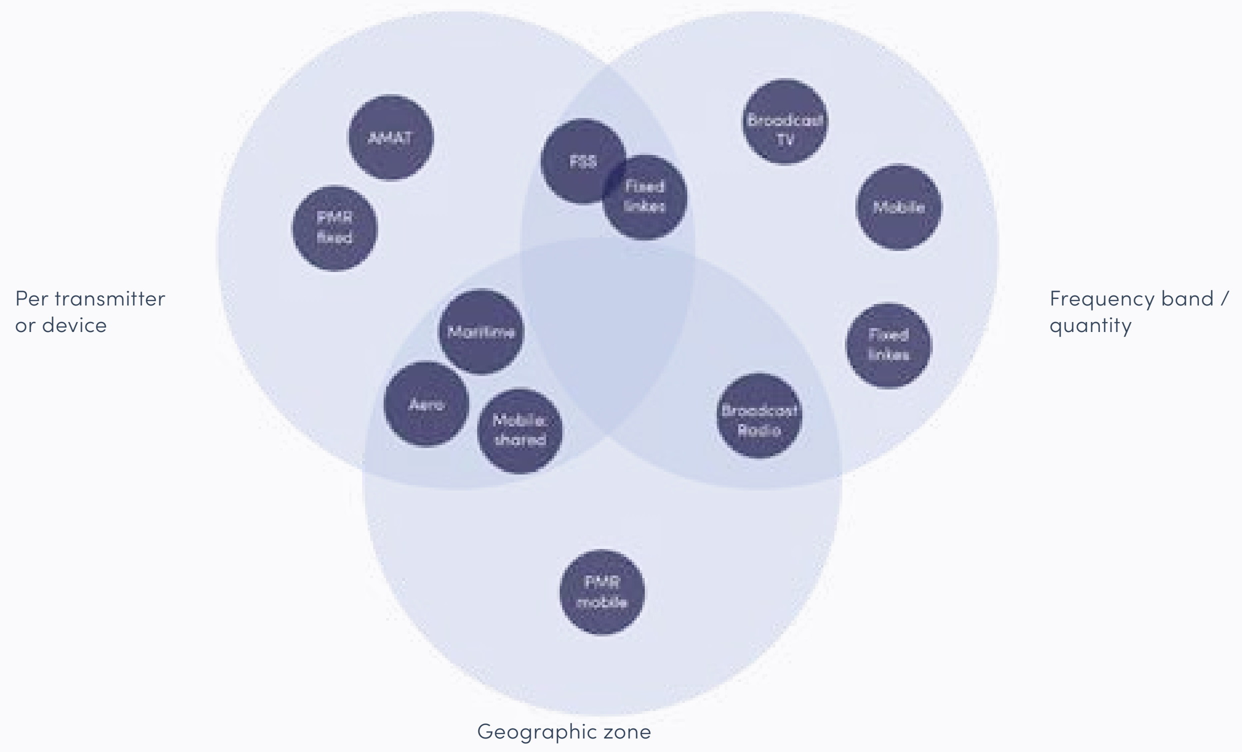



Figure 1: *Approaches to spectrum licencing. This provides a simplified framework, rather than mapping all possibilities. There may be other conditions, such as acceptable power levels, which can be applied to any licence. There are some cases where spectrum is unlicenced (e.g. WiFi, Bluetooth or NR-U).*

[12]The United Kingdom Frequency Allocation Table, updated 2023, The United Kingdom Frequency Allocation Table - Ofcom, March 2023.



When licencing a specific device, the fixed nature (e.g. ground stations) or wide-ranging movement (e.g. aircrafts) of equipment enables more precise planning. In contrast, when a frequency band has been allocated to a particular service, like mobile use in the 900 MHz band, specific portions are typically assigned to companies through competitive processes like auctions. These licences come with conditions protecting other users, while giving operators flexibility in network design within those parameters. Geographic licencing represents a third approach, where spectrum use is authorised for specific areas, enabling frequency reuse across different locations.

Licences are often a combination of these approaches. A geographic zone may be inserted into a nationwide mobile licence, to stop mobile base stations being deployed close to a military base.

An example of combining geographic, device and frequency requirements is Ofcom's approach to Shared Access Licences in the 3.8 – 4.2 GHz range[13]. These are designed to support deployment of private 4G or 5G networks, rather than relying on public network operators. Combining approaches often unlocks more efficient outcomes.

Different spectrum users need different levels of protection from interference. Ofcom groups these into three categories: everyday consumers, businesses, and public services – each has a different risk appetite. Setting fees based on the protection level could encourage users to opt for lower fees and invest in improvements to their own equipment's performance. Creativity in policy making and incentive structures is a tool that can boost spectrum utilisation.

[13]Ofcom, Shared Access Licence: Guidance document, Sept 2022

### 2.2.2 Key sectors and stakeholders

Spectrum covers five key sectors, and stakeholders fall into four main groups (Figure 2):

**Policy & management:** those responsible for managing the spectrum

**Service providers:** entities delivering spectrum-dependent services and capabilities

**Suppliers:** those providing equipment or services to the spectrum users

**End users:** those using the service.

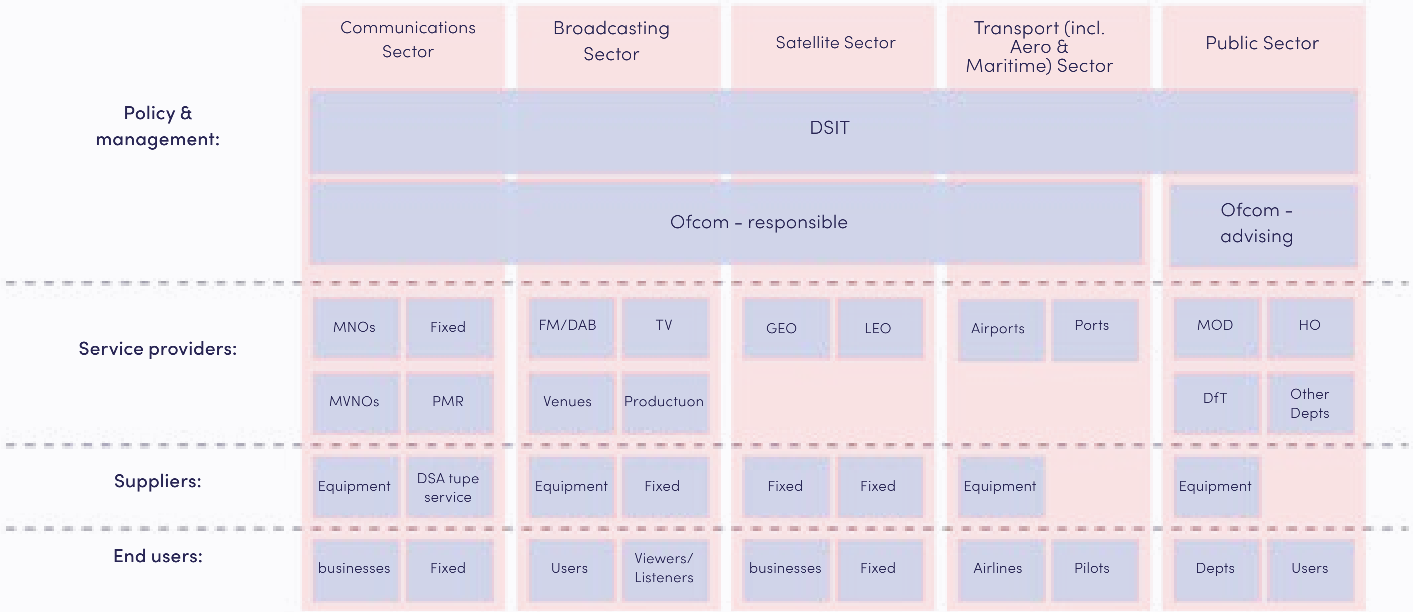



*Figure 2: The five key sectors and four key stakeholder groups in spectrum management.*

This overview provides a practical basis for analysis, informing where AI may be introduced to spectrum management and structuring inputs to consider for a future Cost Benefit Analysis (CBA), discussed in detail in Section 5.



## 2.3 Spectrum management challenges

**Ofcom's Spectrum Roadmap charts a course towards efficient, flexible and universal wireless connectivity. Based on this, and policies and priorities explored in the previous section, we identify five specific challenges of managing spectrum which capture the complexity of balancing competing demand whilst supporting access and innovation.**

**CHALLENGE 1:**
**DRIVING IMPROVED, AFFORDABLE CONNECTIVITY**

Ofcom's vision for wireless connectivity, and their commitment to spectrum efficiency, hinges on high-quality data (one of their future-work themes) to inform metrics for decision-making – namely, Key Performance Indicators (KPIs). The effectiveness of coverage obligations and the selection of appropriate KPIs directly impacts how close we can get to the goal of universal connectivity. A key question centres on data:

*What data should we collect, how should we collect it, and how can AI and advanced analytics help inform better policy decisions?*

**CHALLENGE 2:**
**MONITORING FOR LICENSING AND COMPLIANCE**

While Ofcom emphasise the need for flexible access, current licensing processes can be inefficient, time-consuming and potentially stifle innovation. The reactive nature of spectrum monitoring means interference to other services is often addressed in retrospect. Inefficiencies in licensing and monitoring processes create barriers to rapid spectrum access, risking undermining both efficient utilisation and the protection of existing users. We ask:

*Can Ofcom use AI to enhance licensing efficiency, to improve consistency and lower regulator costs of granting licences?*

*Could AI transform spectrum interference monitoring from reactive to predictive?*

**CHALLENGE 3:**
**MANAGING INTERFERENCE IN SHARED SPECTRUM**

Overly conservative approaches to interference management lead to valuable spectrum being unused. Ofcom aims to increase flexibility, but limitations in traditional interference modelling and a lack of real-world measurement data may restrict sharing opportunities. This raises questions:

*Could data-driven approaches enhance interference management while safeguarding existing users?*

*Can other datasets be used to provide proxy data where direct measurements are scarce?*

CHALLENGE 4

**DEFINING EFFICIENT SHARING FRAMEWORKS**

Ofcom prioritises flexible spectrum use, but the challenges of coordinating different services and the administrative burden of managing shared access can lead to overly restrictive protection measures. When combined with the prevalence of national licences, these approaches may lead to spectrum lying dormant in many areas where it could be safely used. This raises important questions:

*How might data from international approaches, like the US CBRS system, inform more dynamic spectrum sharing in the UK?*

*Where spectrum sharing relies on interference predictions, would better modelling allow us to reduce mandatory protection measures while maintaining quality?*

CHALLENGE 5:

**UNLOCKING EFFICIENT ALLOCATION OF PUBLIC SUBSIDY WITH DATA**

Current approaches to public subsidy in spectrum management suffer from a critical data gap. Ofcom strives for universal connectivity and emphasises the importance of improved data for spectrum decisions. However, effectively targeting public subsidies is curbed by limited insights into how allocation, coverage costs and actual connectivity impact one another. Traditional datasets may not capture the interplay of policy decisions and their impact on private sector investment (particularly in underserved areas). International sources, particularly US auction data and subsequent reporting of coverage obligations, could provide valuable insights – but translating this to inform UK policy decisions requires sophisticated analysis. We ask:

*How can we better leverage international spectrum management data to inform UK decisions about public investment in connectivity?*



## 2.4 Opportunities for AI to enhance spectrum management

**Having identified these challenges, we must systematically examine the UK spectrum landscape to assess where AI and advanced data analytics could have the most significant impact in addressing them. The UK spectrum landscape (Figure 3) we present below is a flexible model that applies to spectrum managers worldwide, whilst also accommodating regional variations (e.g. some regions might focus on administrative assignments rather than auctions). We identify three principal domains:**

- **Processes:** Ongoing tasks that follow clear, repeatable sequences
- **Projects:** Time-bound initiatives with defined endpoints, representing focused efforts to achieve specific goals
- **Capabilities:** Core competencies that an organisation must develop and maintain to excel, both in day-to-day operations and special projects

Examining this landscape, we identify five primary areas for introducing AI in UK spectrum management (labelled 1-5 in the Figure). The nature and frequency of activities is key for assessing where AI can deliver value. Frequent, repetitive tasks may justify the use of AI on an on-going basis.

Rare but complex activities, such as optimising efficiency in a one-off rearrangement of spectrum use, will require a different approach. This distinction may be important in guiding Ofcom's decision around developing AI expertise in-house or partner with external specialists.

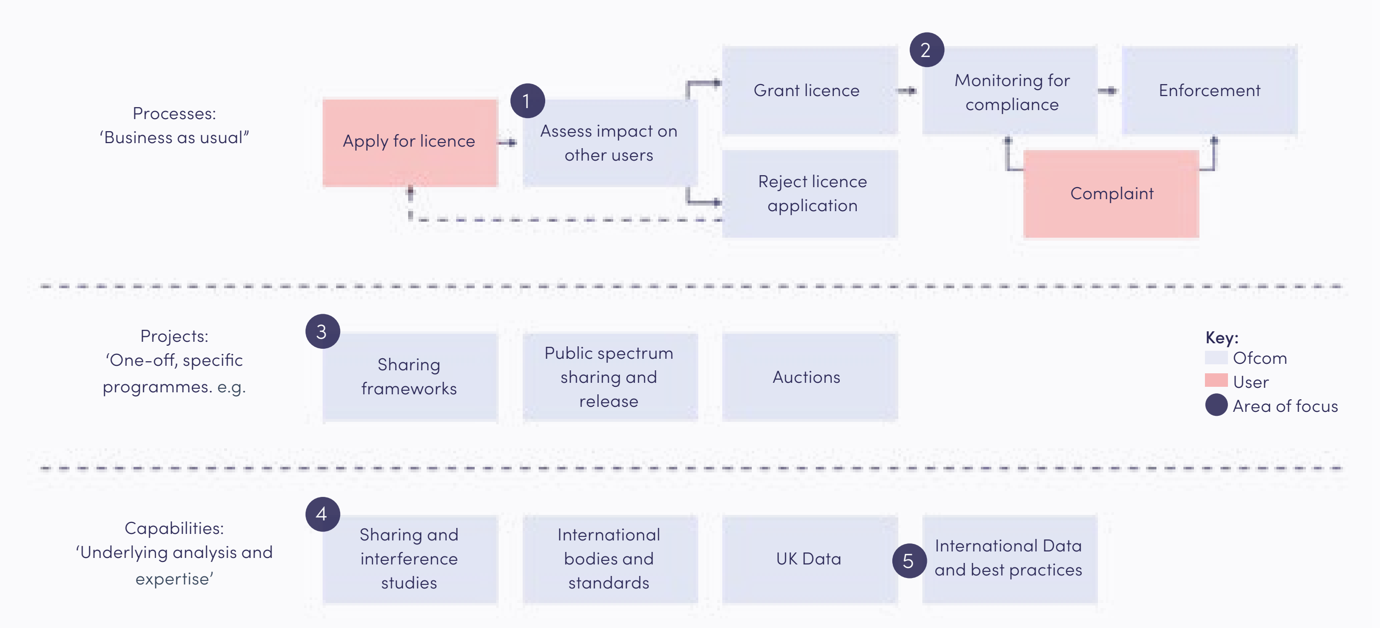



*Figure 3: The UK spectrum landscape, from the perspective of Ofcom.*

These areas are expanded upon below and inform our recommendations of how AI can be introduced to spectrum management (in section 4).

### 1. ASSESS IMPACT ON OTHER USERS IN ASSIGNING LICENCES

Derived from Challenge 2 and 3, this opportunity addresses a key process in spectrum management: the assessment of interference impact when issuing new licences. Current processes rely on interference models that, while protective to existing users, may be overly conservative and restrictive. AI could transform this process.

AI could enable more dynamic, data-driven interference predictions. It could also extend self-service licensing through intelligent automation. For some licence types, self-service portals already exist to streamline parts of the process. AI could extend this, allowing users to make intelligent trade-offs based on their interference tolerance and protection needs. This could lead to more efficient spectrum use while maintaining appropriate protection for existing users. The approach could also incentivise improved receiver performance through more flexible, risk-based licensing.

### 2. MONITORING AND COMPLIANCE

Building directly on Challenge 2, this opportunity addresses both efficient licence management and Challenge 1's KPI monitoring needs. Currently, compliance monitoring varies by licence type – from mobile operators' self-reported signal strength verified through drive tests, to reactive investigations for fixed links, to continuous monitoring for critical systems like airport communications.

As sensors become cheaper and easily connected, AI could transform compliance monitoring from reactive to proactive if the challenges around who deploys, maintains and analyses the sensor data can be overcome. AI algorithms could analyse real-time data to flag potential issues before they impact services, while simultaneously optimising cases of expensive verification methods like drive tests.



### 3. SPECTRUM SHARING FRAMEWORKS

Emerging from Challenge 3 and 4, this opportunity explores how AI could enhance dynamic spectrum sharing approaches while building trust among stakeholders. The US CBRS experience demonstrates that initially conservative protection measures can be relaxed once real-world data proves interference risks are lower than predicted. However, implementing such frameworks faces two key barriers: data ownership and system costs.

The system cost challenge raises questions about infrastructure investment, device compatibility, and whether uncertainty about spectrum access poses a greater barrier to adoption than previously assumed. The data ownership challenge creates a closed loop problem – better decisions require better data, but data collectors may differ from system users. AI could help break this loop by analysing real-world commercial data to validate or refine modelled predictions. This can help to build trust, while maintaining robust frameworks to protect sensitive information.

### 4. SHARING AND INTERFERENCE STUDIES

Addressing Challenge 3 and 4, AI could transform how we predict and manage interference between services. For fixed sites like radio telescopes and radar installations, AI models could combine weather data, terrain information, and historical patterns to optimise protection zones. This would move beyond current conservative approaches to create more dynamic, efficient sharing arrangements.

Looking ahead to the WRC 2027's consideration of new mobile bands (4.4-4.8 MHz, 7.125-8.4 MHz, 14.8-15.35 MHz), which are currently used significantly by UK military, AI could accelerate the analysis of international interference studies. This is particularly relevant, given Ofcom needs to balance global harmonisation benefits with protecting existing users. AI analysis of international data could help develop evidence-based recommendations.

### 5. UK AND INTERNATIONAL DATA BEST PRACTICES

Drawing from Challenge 5's emphasis on learning from international experiences, while also supporting Challenge 1's need for better data-driven decision making, this opportunity focuses on developing robust frameworks for data collection, analysis, and sharing. Existing studies examine correlations between spectrum decisions and outcomes, but they often support predetermined positions rather than offering objective insights.

AI could transform how we analyse spectrum effectiveness, inform public subsidy decisions, and uncover previously hidden relationships between communications infrastructure and broader social outcomes. Through techniques like proxy data analysis, we could better understand how spectrum policy decisions impact areas ranging from education to healthcare access, enabling more evidence based spectrum management.

## 2.5 The future of spectrum management

Spectrum management traditionally follows careful, methodical processes, to prevent interference and ensure reliable communications. This measured approach contrasts with the rapid development of AI, and its growing capacity to tackle complex challenges.

The UK has a unique opportunity to pioneer AI-driven spectrum management. The government's AI Opportunities Action Plan[14] emphasises leveraging AI for economic growth and public service improvement, and Ofcom's Spectrum Roadmap, as referred to on page 5 above, highlights the importance of embracing new technologies, innovation and leveraging data for improved spectrum management. Furthermore, the UK's active voice in international forums like the G7 summit[15] demonstrate the nation's commitment to global collaboration on AI and technology. This international engagement could pave the way to sharing best practices and innovations in spectrum, to enable the fulfilment of future spectrum needs such as 6G.

AI-driven spectrum management will maintain necessary safeguards while accelerating innovation. We seek to turn this opportunity into reality, investigating which AI techniques offer the most promise for spectrum management's unique challenges and complexities.

[14]Department for Science, Innovation & Technology, AI expert to lead Action Plan to ensure UK reaps the benefits of Artificial Intelligence - GOV.UK, 2024

[15]Department for Science, Innovation & Technology, G7 nations to harness AI and innovation to drive growth and productivity - GOV.UK, 2024



# 3 Promising AI techniques for spectrum management

**While AI's application to spectrum management is still in its early days, its transformative potential is vast. From deep learning to digital twins, there is a diverse range of possible applications. In this section we explore potential AI technologies that may apply to spectrum management, drawing insights from research, international trials, and proven techniques across industries.**

We examine both current capabilities and emerging opportunities, evaluating cutting-edge approaches like continual learning systems that adapt to changing conditions, while addressing key considerations of **explainability** and **validation**. By integrating lessons from global spectrum management with proven AI solutions from other sectors, we provide a vision for transforming UK spectrum with AI. To set the stage, the following subsections provide a high-level overview of techniques we subsequently refer to, illustrating how they apply to wireless communication and spectrum management challenges.

## 3.1 Introduction to AI techniques

**Below we summarise the AI landscape, from broad categories of ML techniques to specific architectures and approaches relevant to spectrum management use cases. The AI landscape is far broader that the methods highlighted below, with techniques emerging frequently. Applications of the following techniques are discussed in further detail in this report's sections that follow.**

There are several fundamental approaches to machine learning. Two of these are supervised learning and unsupervised learning. Supervised machine learning uses labelled training data, where the desired output is known, to learn patterns and make predictions. Unsupervised learning, in contrast, works with unlabelled data to discover patterns and structures within the data itself. Another fundamental ML approach is reinforcement learning (RL), which involves an agent learning optimal actions through trial and error in an environment, receiving rewards or penalties for its choices.

A prominent tool for recognising patterns in complex data are neural networks (NNs). These are systems of layers of interconnected nodes, inspired by the structure of the human brain. Deep learning (DL) is a specialised subset of neural networks, comprising multiple layers. It is popular due to its ability to extract intricate features from large datasets, often outperforming traditional methods in tasks involving pattern recognition and data analysis. As data passes through the network, each layer extracts increasingly complex relationships.



**Deep reinforcement learning (DRL)** is a method combining deep learning with an agent that continually learns by interacting with its environment. The agent is rewarded for good decisions and penalised for poor ones, gradually reinforcing preferred behaviour. DRL gained traction for its ability to solve complex sequential decision-making problems and adapt to new environmental situations.

The approach is well suited to complex, well defined problem spaces, as demonstrated by DRL achieving superhuman performance in games such as Atari, Go (AlphaGo), and Chess (AlphaZero)[16]. Its application requires either a 'live' interactive environment with clear, frequent reward signals, or decision-making settings with large amounts of labelled training data, making it well suited to use cases in finance, energy, self-driving vehicles, or robotics.

**Convolutional Neural Networks (CNNs)** are a type of deep learning algorithm with a specific network architecture designed primarily for processing and analysing visual data. They have become a cornerstone in the field of artificial intelligence and machine learning, particularly in computer vision tasks. Containing convolutional layers, the structure allows the network to learn hierarchical features, with earlier layers detecting simple patterns like edges and textures, and deeper layers identifying more complex features and objects.

CNNs generally benefit from large datasets to achieve optimal performance, however, the strengths of CNNs is their adaptability to new problems through transfer learning. Pre-trained CNN architectures like VGG-16, ResNet50, and InceptionV3 can be fine-tuned for new tasks with relatively little data. This feature makes CNNs particularly useful for those looking to apply AI to novel problems without the need for massive datasets or extensive computational resources.

**Generative AI** models are a subset of artificial intelligence that learn the underlying distribution of training data to generate new, similar data samples. These models have become increasingly relevant in the AI and ML landscape due to their versatility and wide range of applications, including text and image generation, anomaly detection, simulation, and forecasting.

Many generative models rely on the Transformer architecture, the foundation for large language models (LLMs) like GPT-3/4, which have achieved state-of-the-art performance across numerous tasks. Through a self-attention mechanism, sequential data is processed efficiently to capture contextual relationships between elements in a sequence. They are widely used because they can be readily adapted to new purposes.

Autoencoders are a type of neural network architecture designed to learn efficient representations of data through unsupervised learning. In contrast with supervised learning, the unsupervised equivalent does not require data labelling, reducing costs at the expense of accuracy. An autoencoder consists of two parts: an encoder that learns to compress input data into a compact representation, and a decoder that attempts to rebuild the original input from the compressed form.

The encoder is trained on normal data and learns to reconstruct typical patterns. When anomalous data arrives, its patterns do not match the normal data, so the decoder produces a poor reconstruction. The difference between the input and the reconstructed output – referred to as the reconstructed error – can then be used to identify anomalies.

[16] Silver et al, Mastering Chess and Shogi by Self-Play with a General Reinforcement Learning Algorithm, Dec 2017.

## 3.2 Current uses of AI for spectrum management

**There are many existing demonstrations of the diverse application of AI in spectrum management, from using the world-leading Gurobi optimiser to fairly allocate spectrum licences, to using deep neural networks for live spectrum analysis. These applications address a variety of challenges, from network traffic prediction to spectrum allocation. In this section, we examine current techniques, evaluate their practical limitations and highlight the key challenges of trust and validation.**

### 3.2.1 Deep learning

Deep learning (DL) has already been explored in spectrum management, outperforming conventional methods in predicting mobile network traffic[17,18], detecting radiofrequency signals[19], spectrum sensing[19,22,23], dynamic spectrum allocation[19], and dynamic spectrum access[17,20]. The latter two examples use deep reinforcement learning, developing a decision-making policy using training examples.

Deep learning is powerful. In many cases, it out-performs conventional methods even with missing data or incomplete information. For example, deep learning has been used in recent years to detect radiofrequency signals with incomplete network information[19]. The fact that incomplete data may not present a barrier to AI-enabled solutions is encouraging.

Autoencoders are being used in monitoring to identify anomalies in spectrum usage[17,21]. They show promise for wider application in monitoring and compliance, by way of taking a proactive approach to interference management. They could unlock the detection of subtle precursor patterns, or early warning signs, to indicate an impending interference event, even before it becomes obvious through traditional monitoring. For an autoencoder to be able to detect these early warning signs, it requires training on large amounts of data of past interference events.

[17]Zhang et al., "Deep Learning in Mobile and Wireless Networking: A Survey," *IEEE Communications Surveys & Tutorials*, 2019.
[18]Rutagemwa et al., "Dynamic Spectrum Assignment for Land Mobile Radio with Deep Recurrent Neural Networks," *2018 IEEE International Conference on Communications Workshops (ICC Workshops)*, 2018.
[19]BEREC Report on the impact of Artificial Intelligence (AI) solutions in the telecommunications sector on regulation, 2023.
[20]Naparstek et al., "Deep Multi-User Reinforcement Learning for Dynamic Spectrum Access in Multichannel Wireless Networks," *GLOBE-COM 2017 - 2017 IEEE Global Communications Conference*, 2017.
[21]Feng et al., "Anomaly detection of spectrum in wireless communication via deep auto-encoders," *Journal of Supercomputing*, 2017.
[22]MathWorks, Spectrum Sensing with Deep Learning for Radar and Wireless Communications.
[23]MathWorks, Spectrum Sensing with Deep Learning to Identify 5G and LTE Signals.



### 3.2.2 Spectrum sensing

One aspect of spectrum monitoring is characterising occupancy to understand usage patterns for different bands. Spectrum sensing is key to this, detecting signal presence and identifying interference that may affect quality. In recent years, DL has become increasingly popular for various spectrum sensing applications. Techniques such as semantic segmentation neural networks are used to identify and classify different signals within the same spectrum, enabling efficient spectrum sharing, which we outline below.

#### IDENTIFYING RADAR, 5G NR AND LTE SIGNALS WITH MATLAB

Examples from MathWorks demonstrate the power of deep learning for spectrum sensing, for theoretical models, for identifying both radar[22] as well as 5G NR and LTE signals[23]. The former seeks to detect and differentiate between radar and wireless signals, which is key to spectrum sharing in environments where signals coexist. The latter identifies 5G NR and LTE signals in a wideband spectrogram.

Both examples use a semantic segmentation network trained on synthetic data. By using synthetic data, the models can be trained on a variety of signal scenarios. This strengthens their ability to generalise to real-world conditions, improving the detection accuracy and reducing the need for extensive data collection, saving time and money. However, the quality of the model depends on how well the synthetic data matches reality. If the simulated scenarios do not accurately represent real spectrum environments, models may perform poorly in practice. Creating high-quality synthetic data requires significant expertise to ensure it captures all relevant variations and corner cases.

#### CNNS FOR REAL-TIME WIDEBAND SENSING

Another example of DL for spectrum sensing is the DeepSense framework, which uses convolutional neural networks (CNNs) for real-time wideband spectrum sensing, detecting unused spectrum bands to reduce interference[24]. It performs sensing with extremely low latency over large bandwidths, ensuring that tiny spectrum holes are detected quickly, and real-time digital signal processing constraints are met. It claims to maintain high accuracy and flexibility, making it capable of working with different wireless bands and protocols. However, it is acknowledged that low signal-to-noise ratio regimes prove difficult for the classifier. This could be particularly problematic in practice, when signal conditions are poor or inconsistent.

[24]Uvaydov et al, "DeepSense: Fast Wideband Spectrum Sensing Through Real-Time In-the-Loop Deep Learning", IEEE Conference on Computer Communications, 2021.

## 3.2.3 Examples of adopting AI and 6G innovation

Many network operators are innovating to shape the future of connectivity. The BT Group recently announced its approaches with AI, Open RAN, 6G and spectrum management[25]. Their initiatives include AI-Powered Traffic Management which seeks to enhance network efficiency via AI models for real-time traffic optimisation. Vodafone is also embracing Open RAN and AI to optimise networks and prepare for 6G[26].

Nokia Bell Labs is innovating with AI for spectrum sharing in 6G, as more intelligent knowledge systems will need to be combined with robust computation capabilities. This will merge network, application and processor roles.

By integrating machine learning from the environment side, Nokia Bell Labs aims to allocate and share more frequency, to optimise the performance and energy efficiency of next generation wireless networks[27]. Their initiatives include developing mechanisms for interference prediction, notification systems, sensing approaches for interference, and optimising beamforming algorithms.

[25]6G Academy, BT Group's AI, Open RAN, and 6G Innovation: A Deep Dive into Telecom's Future, 2025.
[26]6G Academy, Vodafone's Role in 5G RAN Automation & 6G Future: Open RAN Deep Dive, 2025.
[27]Nokia Bell Labs, AI for Self Organized Networks | Nokia.com.



## 3.3 Global trials and studies

Around the world, users of spectrum and regulators are probing how AI might improve current processes. Early initiatives range from India's work with deep reinforcement learning to the UK MOD's spectrum demand forecasting. These trials highlight a clear pattern – the most effective approaches are not solely purely AI-driven. Rather, there is a push for combining AI with conventional methods.

### 3.3.1 Key learnings

**Hybrid approaches** that combine AI with conventional methods are widely recommended[47,27,28]. The domain expertise that is built into the conventional method can build trust and compensate for data limitations. Experts in the field can bring a deep understanding of nuances in spectrum management. These insights are key for both effective interpretation of data and AI-based recommendations.

There are some crucial data challenges, including cost and a lack of standardised and granular datasets[28,29,30]. Patterns in spectrum usage datasets can heavily depend on time, geographic location, frequency, and device. It is often not possible to collect a large amount of data at a fine granularity in all four of these dimensions, meaning that important usage patterns are missed. There are many sources of spectrum data, including direct observations, simulated data and crowdsourcing, which are often in different (or non-standardised) formats. This can make it difficult to train AI models on multiple datasets, as the model expects consistent formatting of input data.

[28]RCR Wireless News, Why AI holds major promise for spectrum sharing at scale, April 2024.
[29]Indian Department of Telecommunications, AI in Spectrum Management Report, March 2021.
[30]FCC Notice of Inquiry, Advancing Understanding of Non-Federal Spectrum Usage, Jul 2023.

## 3.3.2 Key trials

Below we outline key global trials where regulators and organisations are adopting AI for spectrum management.

**DEEP REINFORCEMENT LEARNING FOR DYNAMIC SPECTRUM ALLOCATION:**

**Organisation:** The Indian Department of Telecommunications

**Technique & use case:** Deep Reinforcement Learning for dynamic spectrum allocation

**Description:**

In 2021, The Indian Department of Telecommunications (DoT) explores the role of AI in addressing spectrum management challenges, including deep reinforcement learning for dynamic spectrum allocation[28]. This allows users without licence access to idle spectrum allocated to authorised users. DoT were motivated to consider AI for DSM following the success of a 2019 competition hosted by the U.S. Defense Advanced Research Projects Agency (DARPA).

**Insights:** This research project highlights that the DARPA competition developed a collaborative network using Spectrum Monitoring and Spectrum diagnosis, achieving nearly 300% efficiency over current designs.  This competition shows the potential for using AI based tools for spectrum management, highlighting use cases such as: equitable division of resources, incumbent protection, pattern exploitation, convergence on new spectrum use, solutions for changing demands, spatial reuse, and prioritisation.

Generative AI could also benefit this task, specifically in reducing interference and for scenario simulation[31], as well as predicting spectrum demand and increasing available, high-quality data[32].

[31]Analysys Mason, Improved management of shared spectrum: a potential AI/ML use case, Jan 2024.
[32]5G Americas, How Generative AI Could Impact Network Planning, RAN Configuration, and Spectrum Management - 5G Americas, March 2024.
[33]FCC Notice of Inquiry, Advancing Understanding of Non-Federal Spectrum Usage, Jul 2023.



**PREDICTING DEMAND TO INFORM POLICY:**

**Organisation:** Ministry of Defence

**Technique & use case:** Granular spectrum demand prediction to inform policy decisions.

**Description:**

In 2008, MOD trialled AI models to predict their demand for spectrum with a breakdown by time, geographic location, frequency, and device[34].

**Results & benefits:**

The MODs model performance suffered from a lack of data, and key differences between the UK and other countries in proxy data. To overcome these data limitations, approaches to improve the representativeness of proxy data should be explored, with promising candidates including Gaussian process regression models and synthetic data generation techniques. This is discussed at length in the next section.

**DYNAMIC SPECTRUM SHARING:**

**Organisation:** MITRE

**Technique & use case:** Dynamic Spectrum Sharing experiments

**Description:**

The National Science Foundation has granted $10.5m to a research team headed by MITRE for dynamic spectrum sharing experiments[35]. These experiments will test new AI technologies for spectrum sharing. Dynamic spectrum sharing aims to real-time allocation based on instantaneous demand and usage patterns, which enables more efficient spectrum use than static spectrum sharing, where allocation is typically granted at the licensing stage[36].

MITRE have recently launched the ATLAS initiative to collect data on AI vulnerabilities[37]. Models could be trained on this abundance of incident data to detect widespread vulnerabilities, or early warning signs before an incident occurs. MITRE also have access to a new supercomputer called the Federal AI Sandbox, which will be used to train AI systems such as large language models (LLMs)[38].

**Results & benefits:**

An AI supercomputer at this scale is ideal for training new, government-specific large frontier AI models, including LLMs, other generative AI, machine vision and multimodal perception systems, and reinforcement learning decision aids. If applied to spectrum, this could lead to advancements in the scope of AI models in spectrum.

[34]UK Ministry of Defence, Defence Demand for Spectrum Report (2008 – 2027), 2008.
[35]MITRE, MITRE-led Team to Develop Radio Dynamic Zone for Spectrum Sharing Research | MITRE, Nov 2024.
[36]RCR Wireless News, Dynamic spectrum sharing vs. static spectrum sharing, March 2020.
[37]MITRE ATLAS, Navigate threats to AI systems through real-world insights, MITRE ATLAS™.
[38]MITRE, Federal AI Sandbox | MITRE, May 2024.

### 3.3.3 Spectrum sandboxes

As part of DSIT's long term planning to address the growing demand for spectrum and to balance current connectivity needs with future technological advancements, ensuring resilience and adaptability, it is investing £5m in the ongoing spectrum sandbox initiative.[39]

The spectrum sandboxes, set within certain geographic areas, are designed to explore innovative approaches to spectrum sharing under the Shared Access and Local Access Frameworks, and enabling new services and applications, particularly in the upper 6GHz band. The three sandbox projects are exploring:

- **Advancing Dynamic Spectrum Access (DSA):** the Proof-of-Concept DSA system aims at automating and expediting licensing for a Local Access Licence. The prototype DSA solution identified significant under-utilised spectrum and subsequently established practical interference protection thresholds through simulation.
- **Path Loss, Interference, and Economic Modelling:** exploring path loss and interference of the 5.2GHz and 7.6GHz bands focusing on the interaction of spectrum signals with building materials, highlighting the opportunities for the upper 6GHz band to support high-demand scenarios.
- **Tackling Interference and Coexistence:** exploring interference management and coexistence between Wi-Fi and mobile networks in the upper 6GHz band, demonstrating potential new signalling techniques to detect and manage interference, so that both use technologies can co-exist without harmful interference.

The spectrum sandboxes initiatives aims to give spectrum users more freedom to experiment with spectrum sharing technologies[40]. This could lead to innovative technologies that can then be tested at scale. A possible next step is to adopt DARPA's idea of testing sharing technologies in a realistic radiofrequency simulation – known as virtual sandboxes[41]. These could be used to give assurance to the public sector over sharing technologies.

[39]A Guide to the Department for Science, Innovation and Technology's (DSIT), A guide to DSITs Telecoms Research Development Innovation Initiatives, Feb 2024.
[40]The UK Telecoms Innovation Network, Everything you need to know about Spectrum Sandboxes | UKTIN, Jan 2024.
[41]IEEE Spectrum, DARPA's Grand Challenge Is Over—What's Next for AI-Enabled Spectrum Sharing Technology? - IEEE Spectrum, Oct 2019.



### 3.3.4 FCC Notice

In 2023, the Federal Communications Commission (FCC) issued a Notice of Inquiry that sought guidance on open problems in spectrum management aiming to advance understanding of non-Federal spectrum usage through new data sources, technologies and methods[42,29]. There are interesting discussions and questions on how to define a metric for spectrum utilisation, the granularity of data required to generate trust, and how to test the reliability of synthetic datasets[29]. Using advanced tools to understand future spectrum usage can help identify new opportunities to facilitate more efficient spectrum use, including new spectrum sharing techniques and approaches to enable co-existence among users and services.

### 3.3.5 AI for wireless communications in North America

Several companies in North America are pioneering AI for wireless communications. DeepSig, based in the US, uses deep learning to enhance signal processing. Their products include OmniPHY-5G, which transforms 5G Physical Uplink Shared Channel processing by replacing conventional algorithms with a deep neural network[43]. Another of their products is OmniSIG, for automating RF detection, monitoring and analysing the radio frequency environment to find sources of interference or unauthorised signals[44]. OmniSIG uses a trained neural network provides real-time identification, classification, and localisation of known and unknown signals.

Qoherent, an early-stage Canadian startup, is integrating machine learning into software-defined radio systems to transform signal processing workflows[45]. Intelligent radios autonomously adapt to spectral conditions, improving performance in complex environments. Through collaborations, Qoherent is developing tools for signal synthesis, dataset curation, and model training – advancing both AI and quantum computing (QC) applications. Quantum computers harness quantum mechanics principles to perform computations infeasible for classical computers. Unlike traditional bits that can be in one of two states (0 or 1), quantum computers use qubits that can represent both 0 and 1 simultaneously. This enables parallel processing of complex calculations.

Qoherent is exploring the integration of Noisy Intermediate-Scale Quantum devices – current-generation quantum computers with limited qubit counts and connectivity – to enhance ML models for tasks like sampling, optimisation, and quantum machine learning[46]. While QC technology remains largely inaccessible due to high hardware costs, qubit stability challenges, and operational constraints, the field is advancing rapidly.

[42]FCC Notice of Inquiry, Advancing Understanding of Non-Federal Spectrum Usage | Federal Communications Commission, Jul 2023.
[43]DeepSig & Intel White Paper, Amplifying 5G vRAN Performance with Artificial Intelligence & Deep Learning, 2022.
[44]iGR White Paper, iGR RF Awareness for Private Wireless Networks White Paper, 2022.
[45]Qoherent, Qoherent - drive the creation of intelligent radios.
[46]Qoherent Quantum Computing, 2022, Quantum Computing & NISQ Quantum.

## 3.4 The benefits of AI techniques

**How has AI been able to outperform conventional methods? Three key advantages noted in the literature are: autonomy, continual learning, and a clearer understanding of future behaviour[19,47,48].**

Artificial intelligence can continually learn, adapt, and improve. This feature, known as continual learning, means that AI models can be more robust to changes in the radio environment when compared to conventional methods[19]. If there is a fundamental change to the environment, such as different patterns in spectrum usage, then this will be detected and accounted for by the model. This can be programmed to happen automatically, without user input. With a conventional method, it takes time for users to detect a change and manually update the method.

Simulations can inform future decision-making by providing a picture of the benefits and challenges associated with actions[47]. A user can perform scenario analysis by inputting an action, such as a new licensing strategy, into a model, which will then predict future behaviour resulting from this action. Many different actions can be tested, allowing us to discover optimal solutions through systematic experimentation.

### 3.4.1 Trust and validation

Trust and validation must be addressed for widespread support[47]. These requirements stem from both technical stakeholders' need for verification and end users' right to transparency. Trust can be built by using a combination of explainable AI, real-time validation, human-on-the-loop (or human-in-the-loop) capabilities, and thorough documentation[47].

Explainable AI (XAI) refers to methods that explain why an AI model is giving a particular output, predicting a certain value or recommending a particular solution. In prediction models, XAI methods can inform the user which model inputs contributed most, or which features of the data are strongly influencing predictions[49].

Validating AI models in real-time allows immediate action to be taken if performance deteriorates below established benchmarks. Here, human-in-the-loop capabilities step in – a domain expert can take over as soon as model performance drops. Such capabilities can be particularly relevant, for instance, in managing interference for emergency services.

[47]The NITRD Program, Artificial Intelligence & Wireless Spectrum: Opportunities and Challenges, Workshop Report, Nov 2020.
[48]Heikki Kokkinen, Fairspectrum: Artificial Intelligence in Spectrum Management.
[49]Aas et al, "Explaining individual predictions when features are dependent: More accurate approximations to Shapley values," *Artificial Intelligence*, 2021.



### 3.4.2 Overcoming data limitations with synthetic data generation

Spectrum data depends on factors including time, geographic location, frequency, and device. It can be difficult to collect large amounts of spectrum data that is granular in all dimensions, which in turn makes it difficult to train accurate AI models. Synthetic data, generated by AI, may be able to overcome this problem. This method increases dataset size at low cost by generating artificial data that has the same patterns and characteristics as real data[47]. However, the reliability of artificial data is difficult to validate. Spectrum environments are highly complex and dynamic, and real-world interference patterns may not be fully captured in the synthetic data.

There are many ways to generate synthetic data. Two approaches from deep learning are Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs). These methods are often used to generate complex data types, like images or time-series data, and can produce high-quality synthetic datasets in scenarios where real data is scarce. GANs consist of two neural networks – a generator creates synthetic data and a discriminator evaluates how realistic the data is. GANs are known for producing highly realistic data, especially in image synthesis. This could make them ideal for generating spectrogram data. However, training a GAN can be challenging as they require careful tuning and are prone to model collapse – where the generator produces limited varieties of outputs.

VAEs, which are different in their architecture, generate synthetic data based on reconstructions from compressed-input data representations. Because VAEs use a probabilistic framework, unlike traditional autoencoders, the data generated is smooth and controlled in its variability. This is useful in situations that demand diverse data with controlled randomness and therefore could be relevant in spectrum sensing algorithms. To train and evaluate spectrum sensing algorithms, you need diverse data that represents different signal types, noise levels and interference patterns. Using a VAE in this context could help in creating models that accurately detect availability in different environments. However, the data generated from VAEs can sometimes be unsharp or unrealistic, due to the nature of their architecture.

# 4 Recommendations and opportunities for Ofcom

**The recommendations described below are presented in an order that mirrors the key challenges and opportunities identified for Ofcom in the first section of this report. For each recommendation, we describe the benefits, limitations, and possible considerations for practicalities of adoption and implementation.**

## 4.1 AI for licensing applications

Ofcom grants licences in response to applications for various types of spectrum use. Prospective users submit applications, and Ofcom reviews these before granting licences with corresponding conditions. Decisions are based on factors such as interference risk, technical standards, regulations, and public consultations. How can AI be leveraged to enhance the licensing process?

### 4.1.1 LLMs for analysing applications

Initial processing and review of application forms has the potential to be efficiently handled by large language models (LLMs). This would require significant compute power, so the best solution would be to use transfer learning – utilising a pre-trained model (like GPT from OpenAI) and fine-tuning it on a specific, more relevant dataset. For example, fine-tuning an LLM on historical licence application data from the Wireless Telegraphy Act Register (WTR) could create a model that reviews and summarises applications, streamlining this process.



### 4.1.2 Assessing licensing impact

Key variables submitted in licence applications (such as frequency bands, device, power levels, and geographical area) are prime features for feeding into a model that could predict the impact granting a licence would have on other users. In the shorter term, a model could read these variables directly from the current data format in the WTR. In the longer term, it could potentially be integrated with a fine-tuned LLM analysing applications, for seamless data transfer between systems.

These models may be developed on a licence-type basis (see Figure 1) for specificity, or flexible but non-specific general interference-prediction model. Such models could be designed to not only predict interference based on licences and usage patterns, but also make recommendations based on optimal terms, to minimise interference or maximise coverage. This could involve Convolutional Neural Networks (CNNs), Transformer-based architectures, or direct optimisation using approaches like gradient descent, genetic algorithms, and powerful standalone solvers like Gurobi.

### 4.1.3 Automating metric creation

There is a demand for metrics (also known as Key Performance Indicators, or KPIs) in areas intrinsically linked to licensing, such as spectrum utilisation and mobile coverage (see Challenge 1). As in the FCC's extensive discussion on defining spectrum utilisation in their 2023 Notice of Inquiry, it can be extremely difficult to find the optimal definition of a metric[29].

**Feature extraction methods,** such as autoencoders and principal component analysis (PCA), can find meaningful metrics by extracting patterns from data. PCA works by identifying the directions (principal components) along which the data varies most. The results from this analysis would need combining with domain expertise, for a hybrid human-informed approach. Feature extraction could find candidate metrics, and a human user may then choose optimal ones based on utility and interpretability.

Adoption of metrics will be challenging if they are not **interpretable.** For example, if it is not clear why a metric for mobile coverage is suggesting that coverage is lower than expected, then it is unlikely to be trusted. **Explainable AI** (XAI) techniques like SHAP (SHapley Additive exPlanations) can be incorporated into the method, so it is clear which features contribute to the metric and how important each feature is.

In the case of **spectrum utilisation,** there are many different metrics and each of these generate unique insights. Again, it is difficult to determine which metrics are optimal[29]. For example, should frequency band capacity be incorporated into the definition? The FCC defines spectrum usage as 'the extent to which a set of frequencies is being utilised'[29]. Therefore, to gain insights we would require data on the number of spectrum users in specific bands and the capacity of the system.

The more granular the data is in geographic, frequency, and time dimensions, the more accurate the measure of spectrum utilisation will be. Time granularity helps models capture temporal dependencies, such as seasonal effects and other common patterns occurring at certain times of the day, week or year.

The new metric for spectrum utilisation could be used in licensing, to set utilisation requirements and ensure efficient use of limited spectrum resources. It could also be a useful input feature for new AI models in spectrum sharing, such as a model that predicts interference. There is also a demand for improving metrics in optimising spectrum subsidy and pricing policies (see Challenge 5), which is another candidate for this approach.

## 4.2 AI for monitoring and compliance

Ofcom performs monitoring to ensure operators comply with the terms of their licences (see Challenge 2). This is normally reactionary, in response to user complaints, and varies by licence type. When necessary, Ofcom investigates potential non-compliance, which can lead to enforcement actions. These are guided by the Communications Act 2003 and the WT Act 2006, ensuring transparency, accountability, and consistency[9].

### 4.2.1 Optimised sensor installation

As sensors become cheaper and more connected, opportunities for monitoring will increase, in turn increasing opportunities for AI to be introduced. Companies providing monitoring equipment and software for regulators likely already use AI to maximise value (e.g., from expensive drive tests).

Sensors installed by Ofcom in specific areas could provide the most cost-effective solutions. AI may be used to inform decisions on where best to install sensors, based on areas where data is lacking, through Bayesian experimental design (BED). The BED model requires data on existing sensors including their location and performance as well as the viability of new locations.

Two methods of assessing spectrum sensing performance in the literature are probability of detection and probability of false alarm (that is, the probability of reporting a signal is present when it is not)[50]. The model would then use this data to recommend installations that maximise the information gained on the radiofrequency environment. Ofcom should collect performance data from the new installations and update the model, so the model can incorporate this knowledge in future installation recommendation.

As sensors continuously collect data, AI-enabled software will ensure compliance with licence conditions.

### 4.2.2 Proactive monitoring

AI can be designed to automatically and continuously detect and flag suspicious behaviour, transforming current monitoring approaches from reactive to proactive. For instance, recurrent neural networks (RNNs) may be able to identify temporal patterns in monitoring data (from spectrum sensors) that deviate from licence conditions (from the Wireless Telegraphy Register). RNNs are apt for processing sequential data and maintaining context over time, making them ideal for analysing time-series data from monitoring sensors.

Further, these could be combined with a reinforcement learning (RL) model that adapts monitoring sensitivity based on historical compliance data, focusing on where and when violations are most likely to occur. Historical compliance data available to Ofcom that would be valuable for training the model includes monitoring data, investigations of interference events, and enforcement actions. The RL model will then be able to learn hidden patterns in licence violations, which may reveal complex dependencies on time, device, and geographic location. It could then be integrated with the RNN, increasing sensitivity to warning signs that are more closely linked to past licence violations.

[50]Kumar et al, "Analysis of spectrum sensing using deep learning algorithms: CNNs and RNNs", Ain Shams Engineering Journal, 2024.



## 4.3 AI for spectrum sharing and interference management

Spectrum sharing, allowing multiple users or devices to share the same frequency bands, is crucial for maximum efficiency (see Challenge 3). On a device-level, AI can be built directly into systems (like 6G technologies, which in the future may be "AI-native") to predict aggregate interference when assessing how to proceed in a spectrum-sharing scenario. When a device is deciding how to share spectrum, depending on the incumbents, optimisation techniques or reinforcement learning (depending on coherence times) can be used.

### 4.3.1 Predicting interference

Supervised learning algorithms can be trained to learn the relationship between input features, like network configurations (e.g. the direction the antenna is pointing on the base station), spectrum utilisation, transmission power levels of nearby devices, and network loading, and aggregate interference.

A machine learning model could be trained using historical data from a cellular network to predict interference levels based on current network conditions. Several model types could be trained and tested on historical data to find the model with the highest prediction accuracy. Some flexible choices to consider include Random Forests, gradient boosted machines (e.g. XGBoost), and k-nearest neighbours (kNN). These can then be used in real-time to enable spectrum sharing with minimal interference. This requires access to extensive historical data and computational resources to train the model, as well as integration with real-time monitoring systems to provide continuous updates.

Beyond this, Deep Reinforcement Learning (DRL) has the scope to learn optimal policies that maximise performance and minimise interference. A DRL agent could be trained to dynamically adjust the power levels and frequencies of a network based on real-time feedback, optimising usage while minimising interference. Implementing this would require a robust simulation environment to train the agent, as well as real-time data collection and processing capabilities to allow the agent to make informed decisions on the spot.

### 4.3.2 Deep Learning on unstructured data from an Ofcom API

Extensive historical data on interference may not currently exist. Ofcom's upcoming API[11] could provide the answer to this gap. Providing spectrum operators and users with a platform to report interference, and record the relevant parameters to inform predictive modelling, would open opportunities for sophisticated interference modelling. If the API enabled users to input text (e.g. an explanation of the interference problem and the solution) into a free-text field, then a pre-trained LLM could be fine-tuned on this dataset.

Such a model could then be used as an interactive chatbot to recommend potential solutions to interference events. This model could significantly reduce the workload on Ofcom to investigate interference events.

Users would first report their problem to the chatbot and only if the problem is not solved would Ofcom investigate the issue further. The LLM should be updated continuously on new investigation data to remove the need for Ofcom to investigate similar problems in the future.

As Ofcom investigate these events, a human user could input data on which events were most severe. An LLM like BERT that is pre-trained for text classification could then be fine-tuned on this dataset to classify the severity of future interference events. This would further reduce Ofcom's workload and enable them to prioritise resources on the most severe cases of interference.



## 4.4 AI for synthetic data and insights on international data

**Global studies in spectrum management have revealed useful insights that could be utilised in the UK. These insights are especially useful in situations where UK data is limited or does not exist at all. AI can analyse, summarise and possibly even augment these insights so their applicability to the UK context is clear.**

### 4.4.1 Synthetic data with international proxies

In 2008, the UK MOD attempted to predict their spectrum demand using AI[34]. There was a lack of historical UK data, so they used international proxies as an alternative. The regression model did not perform well due to key differences in "defence capability requirements and priorities" between the UK and other countries in the proxy data[34]. The recommendations we make here are motivated by the MOD's efforts. Despite differences between countries, finding ways to share and apply international data would be valuable.

Where there is limited UK data and relatively more international data, AI can increase the size of the UK dataset. Although there may be fundamental differences between the two datasets, the AI model can identify the distinct patterns in each. The model can then use this to augment the international data, so it has the same distinct patterns as the UK data. This method would generate synthetic UK data by using the international data as a proxy, enabling AI models to be trained on large UK datasets leading to higher prediction accuracy.

This recommendation is distinct from the MOD's method, which trained AI models directly on the international proxies. Furthermore, it could be applied to any problem where there is more international data than UK data. The FCC publish fixed and mobile broadband coverage data[51], so predicting mobile coverage is a possible application. Data from the US CBRS approach may also provide an opportunity to gain insights on sharing spectrum between commercial and public sectors (see Challenge 4). The model used in CBRS has demonstrated that both federal users, such as the US Navy, and commercial entities can coexist without significant interference.

An alternative approach is to use synthetic data to increase the size of the UK dataset without international proxies. However, this relies heavily on a very small dataset. It will therefore struggle to capture realistic variation that does not appear in the original dataset. Although there may be fundamental differences between the UK and international data, there may also be some similarities, making the approach more reliable.

[51] FCC National Broadband Map, Home | FCC National Broadband Map

## 4.5 Simulation

Simulations can help us make better decisions. They enable us to more accurately predict future behaviour. For example, it can help us answer the question – would interference improve if we introduced a new AI-enabled sharing technology? We can then use simulations to optimise decision-making. Continuing the sharing example - which sharing technology leads to the best improvement in interference? For simulations to be as realistic as possible, we need to utilise as much relevant data as possible.

### 4.5.1 Simulating low-frequency bands

It is possible to build a simulation of the propagation and attenuation of radio signals as they travel through the radiofrequency (RF) environment. Focusing on lower-frequency bands will make models simpler since we would not need to account for building surfaces, trees, foliage, and other physical obstructions. Notwithstanding, models should be relevant to the frequency range in question, along with incumbents and their operating characteristics.

Useful inputs to the simulation model include data on the frequency of the signal, network configuration, and information on the transmitter and receiver devices (e.g. transmitter power and receiver sensitivity). The model could be used to predict coverage areas, identify potential interference zones, and allocate frequencies in a way that reduces the likelihood of interference. This idea requires frequent data updates.

### 4.5.2 Taking inspiration from DARPA

Ofcom could emulate DARPA's idea of testing sharing technologies in a realistic RF simulation[41]. This idea would require Ofcom to develop a mechanistic model (as opposed to a data-driven model) incorporating the physics of radio signal propagation. The model should simulate the RF environment in a specific geographic location, like a suburb of London, inspired by DAPRA's use of downtown Austin, Texas. New AI-enabled sharing technologies could be tested fairly – under fixed conditions – in a realistic setting before introduction into important real-world scenarios. Building a simulation model with the same complexity as DARPA's Colosseum emulator could take several (1-2) years.



## 4.6 Digital twin of the radiofrequency environment

There may be opportunities for Ofcom to work with industry partners to develop a digital twin of the real-world RF environment. This model would provide a realistic simulation of the real-world to use as a testbed for new ideas before introducing them to the real world.

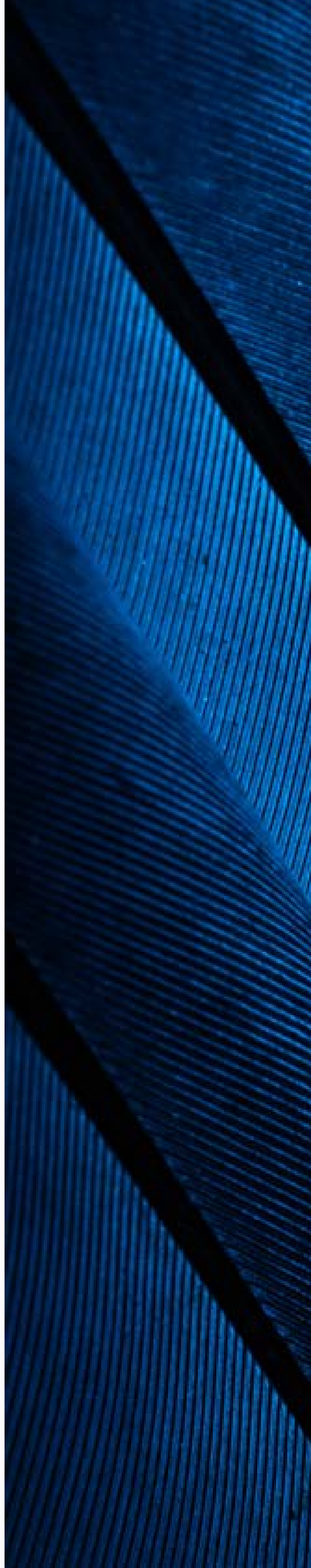
Digital twins extend the idea of virtual sandboxes and the simulation models from the previous section. Instead of simply testing sharing innovations in a specific frequency band, any technology or policy could be tested with any combination of time, geographic location, frequency, or device. This could be further extended to streamlining testing of new licensing strategies and AI-enabled sharing technologies, reducing costs of mobile coverage tests, and assuring the public sector on the large-scale viability of sharing innovations.

Digital twins have revolutionised many industries. For example, smart cities have improved traffic management and optimised the introduction of new roads, while the Climate Resilience Demonstrator (CReDo) has enhanced flood risk management[52].

However, digital twins are a long-term solution. The model requires many real-world conditions, from weather conditions to physical obstructions like buildings and trees, to be built into it. When in operation, it will need close to real-time data updates to be a true 'twin' of reality. Like most digital twin projects, this project could take approximately ten years to finalise. It would be sensible for Ofcom to start simulation work with the ideas from the previous section, and then potentially develop these models into an all-encompassing digital twin.

[52]Digital Twin Hub Climate Resilience Demonstrator (CReDo), Climate Resilience Demonstrator – Digital Twin Hub.





## 4.7 Summary table of recommendations

A summary of our recommendations is outlined below, illustrating the AI technique recommendation, the spectrum use case application, potential benefit to Ofcom and an estimation of implementation horizon.

| RECOMMENDATION | USE CASE | AI TECHNIQUE | BENEFIT | IMPLEMENTATION HORIZON |
|---|---|---|---|---|
| AI for licencing applications | Application processing and review automation<br><br>Licencing impact assessing and granting recommendations<br><br>Spectrum utilisation and developing metric/KPIs | Fine-tuned LLM<br><br>Custom ML model (CNNs, Transformers, etc)<br><br>Feature extraction methods (PCA & XAI) | Improve licencing efficiency and consistency<br><br>Automated licencing suggestions, reduced regulator workload<br><br>Explainable metrics for more sophisticated policies, licencing and subsidies, in turn encouraging efficient operator behaviours | Short-term |
| AI for monitoring and compliance | Optimal locations for new sensor installations<br><br>Automated flagging of licence violations<br><br>Pre-emptive detection of suspicious behaviour | Experimental design (BED)<br><br>Custom ML model (e.g RNNs)<br><br>RL | Enhanced monitoring data collection<br><br>Proactive monitoring, enforcing compliance to support spectrum sharing<br><br>Flag suspicious behaviour before licence violations occur | Long-term for optimised sensor installation<br><br>Short-term for proactive monitoring |
| AI for spectrum sharing and interference management | Predicting interference events to support spectrum sharing<br><br>Chatbot for interference event response | Random Forests, XGBoost, kNN, DRL<br><br>Fine-tuned LLM (e.g. BERT) | Minimising interference in-real time to exploit idle spectrum, boosting spectrum utilisation<br><br>Reduced workload on Ofcom to investigate interference | Medium-term |
| AI for synthetic data and insights on international data | Automated analysis, summaries, and augmentation of international data<br><br>Technology monitoring and adoption statistics for policy making | Generative AI (LLMs, Transformers, etc)<br><br>LLM-enhanced search | Uncover links between infrastructure and end-user experiences (or broader social outcomes)<br><br>Use this analysis to inform more efficient distribution of public subsidy in the UK | Medium-term |
| Simulation | Radio signal propagation and attenuation prediction<br><br>Emulate US sharing technology tests in simulation | Custom ML model<br><br>Simulation techniques | Support spectrum sharing and licence allocation to mitigate interference<br><br>Test new sharing technologies to increase TRL | Short-term for simulating low-frequency bands<br><br>Medium term for DARPA-inspired simulations |
| Digital twin of the UK radiofrequency environment | Create an all-encompassing digital twin of the RF environment to enable comprehensive testing of new sharing technologies, subsidies, and licencing policies. | | Better-informed policies and technology decisions | Long -term |

*Figure 5: summary table of AI technique recommendations. A recommendation summary table with more detailed considerations is provided in Annex A.*

# 5 Inputs for a Cost-Benefit Analysis

**An important element of this report is to provide guidance around the key assumptions and most appropriate approach needed to carry out a Cost-Benefit Analysis (CBA) of the AI recommendations.**

## 5.1 Objective

**A comprehensive CBA would calculate the expected costs and benefits to Ofcom and the UK Government of implementing the recommended AI techniques. We identify the required inputs and, at a high level, categorise the recommendations into low, medium or high impact. This is intended to be used as a starting point by stakeholders for a comprehensive CBA.**

To achieve the widest benefits to consumers and citizens a CBA should avoid a heavy focus on the impact on specific stakeholders. These externalities are key to robust public sector decision-making, and we recommend using the Treasury's 'Green Book' methodology to ensure they are fully considered[53].

Social or public value includes 'all significant costs and benefits that affect the welfare and wellbeing of the population, not just market effects.'[53] So, this may include environmental, cultural, health, social care, justice and security effects. This is essential for important policy decisions affecting many stakeholders and users.

[53] HM Treasury, The Green Book, 2022.



## 5.2 Proposed approach for a CBA

**When considering the viability of future AI-driven projects we propose applying a CBA framework as follows:**

- Agree high level timescales over which to carry out each assessment, gathering relevant stakeholders and assumptions
- For each option, compared to the baseline 'Business as Usual' (BAU: the counterfactual) case of no AI adoption:
  - Quantify the costs and timings for each set of stakeholders (as far as possible in monetary terms)
  - Assess and estimate the benefits and timings value for each set of stakeholders (as far as possible in monetary terms)
- Carry out Cost Benefit Analysis (CBA) by calculating the Net Present Value (NPV) of each by discounting the values using a suitable discount factor, known as the 'social time preference rate (STPR).

## 5.3 Key challenges

**We highlight below some of the challenges faced when developing a comprehensive CBA:**

### 1. ASSIGNING FINANCIAL VALUES TO BENEFITS

It is often relatively straightforward to apply a financial value to the costs of applying AI, such as computers, software, hosting, security and staff time. However, the benefits[54] which may result are often harder to quantify.

### 2. DETERMINING THE APPROPRIATE DURATION TO CARRY OUT THE CBA

A shorter-term CBA may miss crucial long-term benefits, while a longer-term CBA introduces more uncertainty.

### 3. SELECTING A SENSIBLE COUNTERFACTUAL

It is important to set a realistic BAU counterfactual, with which to compare the AI technique. The scenario representing 'AI adoption' is likely to be optimistic and impact defined. At an early stage the requirements and anticipated benefits of the new system should be clearly defined and agreed with stakeholders and system users. The 'no AI adoption' scenario can be based on operational data forecast against known trends and emerging challenges.

### 4. PROBABILITIES AND ATTITUDE TO RISK

In general, the NPV of a small cost with high likelihood may be the same as that of a large cost with very low likelihood. In the case of a public body, however, it will be crucial to take account of the reputational damage and risk of litigation resulting from a significant cost. Estimating the NPV of these factors may be difficult.

### 5. PRESENTING THE RANGE OF POSSIBILITIES

The range of plausible scenarios should be explored and presented along with the sensitivities around key assumptions. These should be incorporated into uncertainty estimates of any cost or benefit. Guiding the decision-makers around how to interpret the CBA is a critical part of the process.

[45]It is good practice, following Green Book guidance, to separate benefits into (i) direct public sector benefits (to Ofcom), (ii) indirect public sector benefits (to other public sector organisations) and (iii) wider benefits to UK society (e.g. individuals, businesses).



## 5.4 Consideration of CBA inputs for AI recommendations

**In Annex B we provide an indication of the relevant inputs – costs and benefits – that would need to be considered for each of our recommended applications of AI. Our initial characterisation of the potential impact (High/Medium/Low) is, at this stage, a high-level indication. Further detailed analysis would be needed to understand the costs and benefits in financial terms, as well as their timing, for a comprehensive CBA.**

Below we briefly comment on the relevant positive impact, and associated costs, of applying AI to each of our five recommendation areas.

### 1. AI FOR SPECTRUM LICENSING

Using AI within the licensing process is largely about driving efficiency within Ofcom itself. While there are initial costs associated with developing suitable AI tools, Ofcom would benefit from a significant reduction in staff cost over time as well as more informed and accurate decisions. Other stakeholders would potentially benefit from quicker access to spectrum and lower costs to navigate the Ofcom processes.

Implementing fine-tuned LLMs for licence application, monitoring, and compliance automation requires upfront data acquisition, engineering (cleaning and preprocessing), and management. The fine-tuning process could be applied to open source LLMs, such as Meta's Llama 3 model range[55], or DeepSeek's state-of-the-art reasoning model R1[56].

The high demand for LLM fine-tuning expertise makes in-house AI capability development an expensive venture, particularly as current market volatility makes staff retention challenging. External consultancies offer AI capability both to develop fine-tuned LLMs, or to implement and maintain AI systems for client deployment. Data Science teams within organisations are the responsible owners of such capabilities, whether developed internally or externally, and their overheads include compute costs, salary considerations, and software licences.

An important assumption to make here, in the application of LLMs, is that future systems would not be used to make final decisions (about whether to grant a licence for example, or what protections to put in place) and that the final decision would always be made by a person. If this is not the case the risk of reputational damage to Ofcom, or even legal challenge regarding decisions, would be much higher.

The Information Commissioners Office (ICO) have recently designed regulation restricting the use of autonomous decision-making system when determining an individual's access to public services[57]. This regulation is evolving rapidly, therefore long-term AI initiatives should include regular review points to ensure compliance with applicable regulation and incorporate best practice.

[55]Meta, Llama, Jan 2025.
[56]DeepSeek, DeepSeek, Jan 2025.
[57]ICO, Explaining decisions made with AI, 2022.

### 2. AI FOR MONITORING AND COMPLIANCE

The use of AI to support Ofcom's monitoring and compliance activities is predominantly around internal efficiency, targeting the monitoring to areas where it will be more effective and therefore either saving money or achieving more for less. There may be some longer-term gains for other stakeholders if it is possible to release more spectrum due to improved monitoring.

The costs associated with the sensor optimisation and proactive compliance monitoring include data preparation, model development, and sustainment. The BED approach to optimise placement requires sensor location, performance, and viable new placement data. Model development requires specialist expertise in experimental design, which could be effectively outsourced to produce actionable recommendations in a one-off project. If future sensor placements are anticipated, project specifications could include software deliverables with user guides for repeated use, minimising model sustainment costs.

For proactive compliance, applying AI to automatically and continuously detect and flag suspicious behaviour requires higher model development and sustainment costs. Assuming Ofcom have access to compliance and interference data, whether digital records to be pre-processed or direct sensor data in machine readable format, a suitable model should be designed for deployment. Available options for model development include academic engagement, input from DSIT researchers, or external consultancy. As with recommendation 1. above, AI management and update costs would typically be associated with a Data Science team, including compute costs, compensation, and software licences.



### 3. AI FOR INTERFERENCE IN SPECTRUM SHARING

This involves improving our understanding of different sharing opportunities. For Ofcom, the costs for both the development of AI software and the training required are therefore more significant. Benefits for Ofcom will be better decision-making around sharing opportunities, and this will likely lead to more spectrum being available to stakeholders. It is also likely to have a longer-term benefit in terms of staff engagement, satisfaction and retention, as success would fundamentally change spectrum utilisation, achieving Ofcom's vision of flexible, efficient spectrum use.

This requires access to extensive historical data and computational resources to train the model. Dedicated research will be needed to extract relevant features from network configuration, device transmission, network loading, and aggregate interference data sources. Real-time monitoring systems must also be integrated to provide continuous updates for operational use. The exact model choice must be motivated by representative data, requiring spectrum sandbox technology trials. Finally, pre-deployment it would be advised to stand up a Data Science team with IT support, capable of addressing deployment issues and further developing the new capability via continuous integration and development (CI/CD).

As with recommendation 1., the development of an interference response LLM chatbot would involve much of the same costs as with fine-tuned LLMs for licensing management automation. Assuming historic interference event data can be captured and retrieved seamlessly via Ofcom's API, and a fine-tuned LLM developed on this, additional costs would involve the design and hosting of a chatbot interface. As with LLM fine-tuning, external consultancies offer AI chatbot development services. Costs of the available options should be considered against due diligence information on available suppliers, to ensure the solution is supported and maintained in the long term.

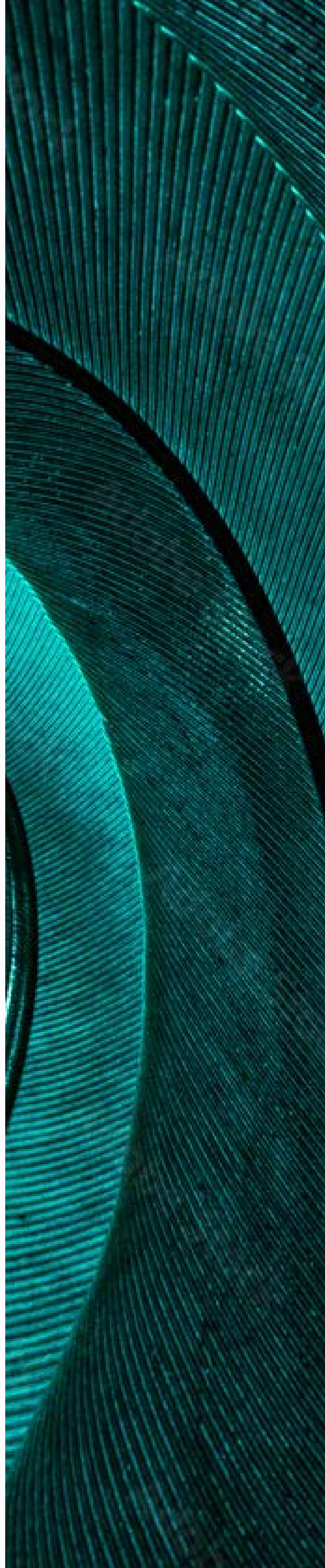
### 4. AI FOR SIMULATING SIGNAL PROPAGATION (ESPECIALLY FOR LOW-FREQUENCY BANDS)

Modelling signal propagation is important when considering mobile coverage and performance. Ofcom could provide better data to users if they are able to supplement data they receive from mobile operators through their own modelling. The long-term benefits of the work could be considerable in terms of better mobile coverage and/or performance for public sector users, citizens and businesses. This may be particularly important for certain public sector users in terms of greater resilience of communication networks. Again, it is important that the final decisions are transparent and justifiable.

Simulation and digital twin development costs are high due to the data, modelling, and maintenance effort required. It is therefore advisable to build from existing commercial software or collaborate with ongoing national digital twin and IoT initiatives. Digital twins for critical national infrastructure are an active area of UK Research and Innovation (UKRI) investment, including the DTNet+ programme led by the Alan Turing Institute.[58] DSIT also support the National Cyber-Physical Infrastructure ecosystem, a government and industry collaboration to amplify innovations.[59] Where possible, Ofcom and wider stakeholder simulation and digital twin work should build from and interoperate with national, industry, and academic initiatives to achieve the greatest long-term benefit.

[58] The Alan Turing Institute , UKRI Digital Twinning NetworkPlus: DTNet+, Jan 2025.
[59] Digital Twin Hub, National Cyber-Physical Infrastructure ecosystem, Jan 2025.





# 6 AI pace, literacy and regulation

**The recommendations made in this report reflect the current state of AI technology, but the pace of innovation in this field is rapid. State-of-the-art is constantly evolving as novel techniques are discovered. New models are continuously being developed and released which outperform their predecessors. Therefore, being agile and adaptable in this environment is an advantage.**

Regularly revisiting and updating procedures, to incorporate the latest advancements, maintains systems at the forefront of AI-driven processes. Continuous maintenance also fosters AI literacy among users, empowering people with the skills and knowledge to use tools effectively and safely. This aspect is consistently emphasised in conversations around responsible technology development. Research from 2023 underscores the need for skills, understanding and access when harnessing AI and data[60].

Aligning with regulatory frameworks is increasingly vital as AI safety policies are developed. The UK government has outlined ambitious plans to support AI adoption, while ensuring safety and ethical standards[61]. There is currently no general statutory regulation of AI in the UK, but the government white paper from March 2023 indicates the first steps towards a framework for responsible AI practices[62]. Their framework is underpinned by five principles: safety and robustness, explainability, fairness, accountability, and contestability[63].

Bias in AI can lead to outcomes involving discrimination, unfairness, or a lack of safety. When explainability is lacking in how large AI models make decisions, this complicates determination of liability when people are adversely affected by automated decisions. The demand for large volumes of data to train AI leads to privacy and data protection concerns, and the compute power required to maintain advanced models also raises environmental and sustainability questions.

Experts stipulate that AI-related legislation may include: mandatory impact assessments, bans on certain applications of AI, and a right for human-intervention to challenge AI decision-making[64]. Future policies may also include allowing open access to underlying code and related documentation, for the sake of transparency and accessibility[65].

AI regulation in the UK is still uncertain. How other countries proceed in setting standards in this area, and how these standards may impact the UK, is also unknown. By staying informed on developments in AI regulation, Ofcom will ensure that systems remain compliant and safe. Beyond this, it will position Ofcom as both a responsible and forward-thinking leader in spectrum management. By embracing AI innovation, and with government backing, Ofcom can lead the modernisation of spectrum management to benefit the UK economy and society.

[60] UK Parliament POST, Data Science Skills in the UK Workforce, Jun 2023.
[61] Department for Science, Innovation & Technology, AI Opportunities Action Plan – GOV.UK, Jan 2025.
[62] Department for Science, Innovation & Technology, A pro-innovation approach to AI regulation - GOV.UK, (updated) Aug 2023.
[63] Department for Science, Innovation & Technology, A pro-innovation approach to AI regulation – GOV.UK, Aug 2023.
[64] UK Parliament POST, Policy implications of artificial intelligence (AI) – POST, Jan 2024.
[65] UK Parliament POST, Artificial intelligence: ethics, governance and regulation – POST, Oct 2024.



# 7 Conclusion

**This report proposes key applications for Artificial Intelligence (AI) in spectrum management, including five priority areas for future developments to address Ofcom, DSIT and broader stakeholder challenges. By considering the policy objectives and long-term vision of spectrum management stakeholders, we present five opportunity areas to unlock value through leveraging AI.**

Our literature review covers a wide array of AI and Machine Learning (ML) techniques of relevance to radio spectrum and telecommunications problem sets. Through a broad definition of techniques, we cover hybrid (AI and traditional) approaches, deep learning, and generative models, discussing their use-cases, data requirements, benefits and limitations.

Setting the UK within an international context, we draw insight from key trials and international studies. We present the potential benefits of AI adoption balanced against practical and governance considerations. Detailing current uses of AI for spectrum management, our future work recommendations are grounded in relevant evidence, qualified against expert consideration of implementation effort and data requirements, and linked directly back to stakeholder challenges.

Our recommendations cover AI applications for licence application, monitoring, and compliance automation; AI for spectrum sharing and interference management systems; AI to expand the exploitable data available for spectrum management; and AI as enablers and users of spectrum simulation and digital twin initiatives. Where appropriate, our recommendations suggest techniques and relevant datasets for future work.

Finally, we propose an approach to undertake a Cost-Benefit Analysis (CBA) for each AI application area, including the process to follow, key challenges and considerations, and relevant costs and benefits for CBA input. We recommend consulting with AI researchers, developers, and system integrators across government and industry to ensure any CBA outputs reflect the current state of the AI technology.

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# Annex A:
# Summary of Detailed Recommendations Table

**In the table below we outline a more detailed summary the implementation requirements for each of our recommendations below, such as input data, algorithm design, process and analysis and actionable outputs.**

| Recommendation | Benefit | Input data | Algorithm design, process and analysis | Actionable output | Implementation practicalities |
|---|---|---|---|---|---|
| AI for licencing applications | Improve licencing efficiency and consistency. | Historical licence application data (from the WTR).<br><br>Number of spectrum users in, and capacity of, frequency bands. | Feature extraction methods (PCA, mutual information, autoencoders) to identify patterns in data.<br><br>Explainability (e.g. SHAP) is key. Metrics (KPIs) can be a contentious topic. | Create explainable metrics for more sophisticated policies, licencing and subsidies. In turn, encourage more efficient operator behaviours. | Short-term |
| AI for monitoring and compliance | Introduce proactive monitoring and optimise sensor installation. | Licencing data (WTR).<br><br>Monitoring data from sensors.<br><br>Historical compliance data.<br><br>Sensor location and performance data. Viability of new sensor locations. | RNNs to identify patterns in spectrum where there is deviation from licence conditions. Combine with RL that adapts monitoring sensitivity based on historical compliance data. Focus on times/places where violations are most likely.<br><br>Bayesian experimental data to optimise locations for new sensors. | Software to flag suspicious behaviour before licence violations occur.<br><br>Optimal locations for new sensors. | Short-term for proactive monitoring.<br><br>Long-term for optimised sensor installation. |
| AI for spectrum sharing and interference management | Prevent and mitigate interference. | Network configurations (transmitter and receiver characteristics).<br>Spectrum utilisation data.<br><br>Network loading data.<br><br>Environmental data.<br><br>Interference data (free text). | Predict aggregated interference.<br>Supervised ML can learn the relationship between input features and the resulting interference (ie the 'target').<br>More sophisticated, Deep RL can learn optimal policies for minimising interference and maximising performance/ utilisation.<br>LLMs to classify severity of interference events and recommend potential solutions. | Optimise spectrum sharing in scenarios where aggregated interference is most unlikely (based on predictive model).<br>Better policy decisions based on insights from RL.<br>Reduced workload on Ofcom to investigate interference. | Medium-term |
| AI for synthetic data and insights on international data | Uncover links between infrastructure and end-user experiences (or broader social outcomes). | International spectrum data | Synthetic data to increase the size of UK datasets using international proxies | Use this analysis to inform more efficient distribution of public subsidy in the UK. | Medium-term |
| Simulation | Predict the propagation and attenuation of radio signals as they travel through an environment.<br>Models for lower-frequency bands are simpler – you need not to worry about build surfaces, trees or foliage etc.<br>DARPA-inspired simulation to test new sharing technologies. | Data on frequency of the signal, network configuration, and information on the transmitter and receiver devices. | Simulated environment for low-frequency bands | Predict coverage areas, identify potential interference zones.<br>Allocate frequencies in a way that reduces the likelihood of interference.<br>Test new sharing technologies, so only the best performing are used in important real-world scenarios. | Short-term for simulating low-frequency bands.<br><br>Medium term for DARPA-inspired simulation. |
| Digital twin of the UK radiofrequency environment | Create an all-encompassing digital twin of the RF environment to enable comprehensive testing of new sharing technologies, subsidies, and licencing policies. | Comprehensive data on many real-world conditions, from weather conditions to physical obstructions like buildings and trees. | A comprehensive simulation model that accounts for many real-world conditions. Real-time data updates required. | Better informed policies and technologies. | Long-term |

# Annex B: Recommended CBA Inputs

**The following table outlines an indication of the inputs for a future Cost Benefit Analysis – costs and benefits – that would need to be considered for each of our recommended applications of AI, showing a characterisation of the potential impact (High/Medium/Low) as an initial high-level indication.**

| | RECOMMENDATION | | | |
|---|---|---|---|---|
| **COST BENEFITS ANALYSIS INPUTS** | 1. AI FOR SPECTRUM LICENCING | 2. AI FOR MONITORING AND COMPLIANCE | 3. AI FOR INTERFERENCE IN SPECTRUM SHARING | 4. SIMULATION FOR SIGNAL PROPAGATION (ESPECIALLY FOR LOW-FREQUENCY BANDS) |
| **COSTS** | | | | |
| Staff costs (development) | M | M | H | M |
| Staff costs (on-going management) | L | L | M | L |
| Computing (hardware or outsourced cloud computing) | | | | |
| **BENEFITS** | | | | |
| Direct benefits to Ofcom | | | | |
| Reduced staff time | M | L | | |
| Reduced spend on outsourced measurements | | H | L | |
| More accurate decisions | L | M | M | M |
| Builds in-house capability | | | L | L |
| Enhanced staff retention | | | L | L |
| **INDIRECT BENEFITS TO OTHER PUBLIC SECTOR ORGANISATIONS** | | | | |
| More spectrum available due to higher efficiency use | | L | H | M |
| Quicker access to appropriate spectrum | M | | M | |
| Less staff time to navigate Ofcom processes | L | | L | |
| **WIDER BENEFITS TO UK SOCIETY (E.G. INDIVIDUALS, BUSINESSES)** | | | | |
| More spectrum available due to higher efficiency use | | L | H | M |
| Quicker access to appropriate spectrum | M | | M | |
| Less staff time to navigate Ofcom processes | L | | L | |
| Better mobile coverage | | | | M |
| **RISKS** | | | | |
| Reputational damage from AI failure | L | L | | L |
| Legal challenge to AI decision | L | | | L |