APPENDICES

Appendix 1. The Radiology Model 2016

Rationale

Current service is unsustainable

The Vision

A collegiate solution

Ability for radiology staff to work across Scotland

Agreed national:
- HR contracts
- clinical governance
- QA

Integrated compatible IT Systems supporting:
- image acquisition, transfer and requests
- data sets and definitions
- transfer of reporting
- agreed patient pathways and protocols
- workforce optimisation
- de-coupling of image capture and reporting
- separation of scheduled and unscheduled activity for both image acquisition and reporting

Objectives

Sustainability of service

Increased resilience of Service

National Radiology Model

Benefits

- Cross boundary reporting
- Improved waiting time performance
- Co-ordinated approach to out of hours
- Support for remote and rural boards in hours reporting
- National approach to radiology reporting
- More effective use of the workforce
- Ability to identify demand, capacity and equipment
- Reduced shortfall in reporting capacity
- Achieving the recognised standard for radiology reporting
- Improved quality of service planning by availability of comparable data
- Flexibility to adapt to emerging clinical service change
- Increased throughput and quality due to de-coupling of scheduled/ unscheduled reporting of images
- Sustain image acquisition close to patient
- Sustain expert radiology opinion to local clinicians
- Cost avoidance
- Cost savings
- Virtual rationalisation

Constraints/ Dependencies/Risks

Constraints/Dependencies

Agreed data sets

Agreed data definitions

National RIS functionality

Ability to report cross boundary

Production of national:
- HR policy
- clinical governance model
- QA model
- integrated comparable IT system
- patient pathways/protocols

Risks

Unsustainable radiology services

Mismatch between demand and capacity

Inability to meet waiting times

Increased costs of private sector for reporting

Recruitment, retention issues

Delayed diagnosis leading to poor patient outcomes

Radiology Model Investment

	(£m)
Capital	**0.67**
Revenue	**2.45**
Non-recurring	
TOTAL	**3.12**

Desired Outcomes

Ensure continuing good outcomes for patients. Sustainable, equitable, access to robust, timely services

Appendix 2. Scottish Health Technologies Group report on Artificial Intelligence

External document prepared by SHTG, part of Health Informatics Scotland (HIS).

Topic exploration

Topic explorations are designed to provide a high-level briefing on topics. The main objectives of this briefing paper are to:

1. Inform discussions
2. Determine the quantity and type of evidence available on a topic
3. Assess whether further review work is required

Topic:	
Date/ Version:	**25/07/19 V3.0**
Topic exploration undertaken by:	Rohan Deogaonkar

1.The decision problem

Describe the decision problem that the topic referrer is seeking to address as you understand it.

Technological advances in computing power and data storage have led to the increased use of artificial intelligence (AI) for purposes of image analysis. The field of radiology is expected to benefit immensely from recent developments in AI, ranging from traditional machine learning algorithms to more advanced deep learning systems which employ neural networks. The implementation of AI in radiology over the next decade will significantly improve the quality, value, and depth of radiology's contribution to patient care and population health, and will revolutionize radiologists' workflows. It is anticipated that AI applications will lead to – workforce optimisation through automation of tasks; improved workflow efficiency through computer aided detection and diagnosis; better disease characterisation through imaging biomarkers; developments in radiomics; and strengthening of data protection.

Given the challenges around recruiting qualified radiology professionals within the NHS, it is imperative that technological solutions which improve existing workforce capacity and exploit the diagnostic/prognostic power of imaging are integrated within workflows. The range of radiology activities impacted upon by AI is large and some applications/technologies are further along the development pathway whilst others are still at their infancy. As part of horizon scanning, there is a need to distinguish between applications which are fit for deployment versus those still in the early research phase.

Provide concise information about the patient population and technology of interest.

Population

Patient condition/disease of interest. Include any information on demographics or other criteria that help define this group e.g. care setting. Basic epidemiology data can be included from ISD.

Potentially any patient undergoing a CT/MRI/ultrasound scan.

Intervention

Describe the technology or intervention to be investigated. Detailed descriptions are not needed unless the intervention is particularly complex or likely to be unfamiliar to colleagues in ERC. If a medical device or procedure, consider at what stage of development the technology is at in relation to the IDEAL Framework. If possible, give an idea of where in a patient pathway, the intervention is intended for use.

AI is a broad term which in radiology refers to methods which excel at automatically recognizing complex patterns in imaging data and providing quantitative, rather than qualitative, assessments of radiographic characteristics. Data aggregation is a key property of all AI systems, as the aim is to transform highly heterogeneous data into data that is homogenous and has an inferred structure. Traditional machine learning (ML) identifies patterns that are present in training sets. In those traditional approaches, it is necessary to compute "features" that are thought to be important factors, which are then used as inputs to train systems to classify images as positive or negative. ML algorithms evolve as they are exposed to more data. Nearly all ML algorithms used to analyse the pixel data of radiology examinations "learn" to give a specific answer by evaluating a large number of exams that have been hand-labelled. This highlights two challenges: 1) adequate labeling of key imaging findings (tedious and time-consuming process); 2) appropriate definition of ground truth (e.g. radiology report, pathology report, clinical outcomes).

Deep Learning (DL) refers to a subfield of representation learning which relies on multiple processing layers, which does not require a human to identify and compute the critical features. Instead, during training, DL algorithms "learn" discriminatory features that best predict the outcomes. This means that the amount of human effort required to train DL systems is less and may also lead to the discovery of important new features that were not anticipated. DL networks have many layers; most systems now have 30 to 150 layers, compared with traditional artificial neural networks which would fail if they had more than about 3 layers. The various layers in these algorithms are used to detect features ranging from simple (e.g. lines, edges, textures, intensity) to complex (e.g. shapes, lesions, or whole organs) in a hierarchical structure. When images are the input, it is typical to use convolutions as input layers. In many cases, one or two convolutional layers will be followed by a pooling layer. A popular pooling function is max pooling which takes the maximum value of the convolutional layer for the region of the image. In this way, max pooling layers identify the most predictive feature within the sampled region and reduces the resolution and memory requirements of the image. It is common to have several groups of convolution and pooling. Numerous network architectures have been developed for general purpose image classification (eg, VGG16, Inception, ResNets). These networks have been typically designed to perform image classification on very large and diverse datasets (eg, ImageNet). Training a neural network involves prompting the algorithm to guess, compare, change weights for a better guess, and compare again, for thousands or millions of

incrementally better guesses, finally reaching a point where more guesses either cease to improve results, or the change in improvement becomes too small to matter.

To be adopted in clinical practice, AI applications must address unmet needs or improve on existing solutions. Clinical AI applications may be conceived as diagnostic tests inserted into existing clinical pathways. AI applications can offer an alternative to current triage (e.g. triage of unread x-rays based on the highest probability of disease determined by an AI algorithm); could replace radiologist input completely (e.g. estimation of bone age by AI software found to consistently provide better performance than a radiologist); or could be an add-on to workflow (e.g. otherwise time consuming activities for patient subgroups best left to ML algorithms).

Alternatively, AI in clinical practice can also be conceptualised in terms of disease characterisation, with applications specifically being used for detection (e.g. identify anomalies within images) or segmentation (defining boundary organs) or classification (e.g. presence of pulmonary embolism in CT scan).

A third way to approach clinical applications is based on classes of use cases. Some of the commonly conceived use cases are: Sorting of normal images from abnormal images; deep-learning based computer aided detection (CAD); Workflow optimization; Quality assurance; Grading and classification; Natural language processing (NLP) and knowledge management.

Radiographic images, coupled with data on clinical outcomes, have led to the emergence and rapid expansion of radiomics. Radiomics is a field of study in which high-throughput data is extracted and large amounts of advanced quantitative imaging features are analysed from medical images. Signals buried within images can be used to augment the traditional radiologic interpretation and gain insights into the structure, behaviour and therapeutic response profile of a disease. Early radiomics studies were largely focused on mining images for a large set of predefined engineered features that describe radiographic aspects of shape, intensity and texture. More recently, radiomics studies have incorporated deep learning algorithms which feature representations automatically from example images and can account for both intra-and intertumour heterogeneity. This has motivated an exploration of the clinical utility of AI generated biomarkers based on standard- of-care radiographic images, and is particularly important when evaluating treatment response in the setting of metastatic disease. To increase the efficiency and fidelity of a radiomics technique, one has to understand which structural or metabolic imaging biomarkers are the best surrogate end points for disease progression and outcomes. Some of the better developed radiomic methodologies exist in the realm of lung cancer diagnosis and prognostication, as well as radiation therapy planning.

Commercializing an AI image analysis product requires understanding the clinical need, or use case; the business case; and new methods of product regulation, verification, and monitoring. There are existing examples of automated segmentation and CAD tools that are not used in clinical practice despite decades of refinement. To overcome barriers to clinical adoption, AI image analysis products must be integrated seamlessly in the clinical workflow and be able to interface with picture archiving and communication system (PACS) software, which may otherwise act as a gatekeeper in the value chain. Further, although AI technology is meant to be broadly applicable, each modality of imaging data (e.g. radiographs, ultrasound, CT, MRI) and disease area will require development of specific strategies for optimal performance. Optimal neural network design and training parameters can vary greatly between data types.

Comparator(s)

Describe the most relevant alternative(s) to the technology being investigated – this should include the current comparator in Scotland. These can be extracted from the topic referral form or from literature identified during the topic exploration. If possible verify that the comparator suggested by the referrer is

relevant for Scotland.

Generally speaking, the comparators are existing clinical workflows which involve manual/non-automated interpretation and verification of radiographic images. In the absence of AI based tools/platforms, radiology will continue to be limited to trained physicians visually assessing medical images for the detection, characterization and monitoring of diseases. More specific comparator(s) can be identified based on the particular AI application or use case being considered.

Outcome(s)

What are the key outcomes of interest to the topic referrer? Do these include appropriate clinical and patient outcomes?

Contingent on use case.

2.Description of evidence available

Briefly describe the best quality evidence available on this topic and give an indication of volume and currency of the evidence. Include mention of any relevant work undertaken previously by HIS or SHTG. A comprehensive literature review is not required, only an indication of the best quality available evidence for further consideration.

There is a fairly large and recent literature base in relation to AI in radiology, but individual studies are largely restricted to proof of concept, validation, and retrospective cohort analysis. Reviews would appear to be focused either on the specific computational method employed or a particular application/ use case. These are listed in the secondary literature section below. No systematic reviews or meta-analyses were identified.

In Scotland, research activity in this area is spearheaded by the *SINAPSE* consortium of universities. More recently, the *iCAIRD* consortium which is a pan-Scotland collaboration of 15 partners from academia, the NHS, and industry has successfully secured funding but details on specific activities are scarce. Some commercial and clinical practice applications are available and have been listed below.

3.Ongoing work in the UK and EUnetHTA

Note ongoing research or projects (if aware of any) on this topic at HIS, NICE, the NHS in Scotland and EUnetHTA.

No ongoing evaluations or HTA's being undertaken by HIS, NICE, NHS or EUnetHTA.

4.Brief literature search results

The following sources are suggestions for topic exploration searches. Note that it may not be necessary to search all sources for every topic.

Resource	Results
[Previous HIS projects on this topic] ***Check if any team within HIS has conducted/ is conducting work on this topic.***	None
UK guidelines and guidance	
[SIGN]	None
[NICE] ***Check for guidelines, technology appraisals, diagnostics, interventional procedures, and medical technologies guidance***	NICE website searched using terms artificial intelligence, machine learning, radiology A medtech innovation briefing was found for VIDAvision for lung volume analysis in emphysema. VIDAvision is a suite of imaging analysis software applications that provides quantitative CT (QCT) lung volume analysis from CT datasets. https://www.nice.org.uk/advice/mib148 A medtech innovation briefing was found for automated radiation dose monitoring software, describing 8 software technologies that analyse patient-level radiation doses from different imaging modalities and examination type. https://www.nice.org.uk/advice/mib127
[Guidelines International Network (GIN)] ***Check for UK guidelines e.g. Royal College Physicians***	Did not check

Secondary literature and economic evaluations	
[ECRI] ***Logins are available from KMT. Use the search option to identify relevant content. Evidence reports and special HTA reports are the most applicable products.***	None
[Cochrane library] ***Check for Cochrane reviews***	No radiology relevant reviews identified with search terms artificial intelligence, machine learning, and neural networks.
[HTA database] ***Limit results to published HTAs using the options on the right of the screen.***	None
Medline ***Check for systematic reviews, meta-analyses, economic evaluations. Use the SIGN search filters for these study designs. Do***	Lundervold (2019) reviews application of deep learning specifically in MRI. Overview of how deep learning has been applied to the entire MRI processing chain, from acquisition to image retrieval, from segmentation to disease prediction. https://www.sciencedirect.com/science/article/pii/S0939388918301181 Fazal et al (2018) – A review of computer aided detection (CADe) of suspicious lesions in mammography; and CAD of lesions & nodules in lung cancer. As well as challenges of CADe. https://www.sciencedirect.com/science/article/abs/pii/S0720048X18302250

not add date limits.	Although not a review, Shaikh et al (2018) contains useful references on the applications for clinical radiomics (e.g. image interpretation, direct image analysis, precision medicine) and defines a strategy for translation of radiomics techniques to commercially implementable enterprise solutions. Part 1 - https://www.ncbi.nlm.nih.gov/pubmed/29366600 ; Part 2 -https://www.sciencedirect.com/science/article/pii/S1546144017316137 LItjens et al (2017) surveyed over 300 publications (2012 -17) on the use of deep learning for image classification, object detection, segmentation, registration, and other tasks. Concise overviews are provided of studies per application area: neuro, retinal, pulmonary, digital pathology, breast, cardiac, abdominal, musculoskeletal. Amongst the studies reviewed, organ (substructure) segmentation was the most prevalent task/activity, MRI was the most prevalent imaging modality and greatest application was for pathology and brain imaging. https://www.sciencedirect.com/science/article/abs/pii/S1361841517301135 Shen et al (2017) reviews the application of deep learning in medical image analysis with particular focus on successes in - image registration, detection of anatomical and cellular structures, tissue segmentation, computer-aided detection and computer-aided disease diagnosis/prognosis. https://www.annualreviews.org/doi/abs/10.1146/annurev-bioeng-071516-044442 Lee et al (2017) provides a review of radiomic studies on lung cancer which quantify several different variables relevant to the imaging assessment of lung malignancy. It summarizes the state of the art for clinical applications for the different classes of currently available radiomic features – morphological, statistical, regional and model-based. https://www.ncbi.nlm.nih.gov/pubmed/27638103 Lubner et al (2017) discusses potential oncologic and non-oncologic applications of CT texture analysis (CTTA). CTTA allows objective assessment of lesion and organ heterogeneity beyond what is possible with subjective visual interpretation. Pre-treatment CT texture features are associated with histopathologic correlates such as tumour grade, tumour cellular processes such as hypoxia or angiogenesis, and genetic features such as KRAS or epidermal growth factor receptor (EGFR) mutation status. In addition, and likely as a result, these CT texture features have been linked to prognosis and clinical outcomes in some tumour types. CTTA CT texture analysis has also been used to assess response to therapy https://www.ncbi.nlm.nih.gov/pubmed/28898189 Isin et al (2016) provide a review of automatic brain tumour segmentation methods using deep learning. 12 studies using deep learning or traditional glioma segmentation methods identified. Performance was compared using DICE scores. Manual segmentation peformed best on core tumor (all tumor components except edema); deep learning methods performed comparably or better to manual for whole tumour and active tumour (only

	active cells) segmentation. https://www.sciencedirect.com/science/article/pii/S187705091632587X
Primary studies (only if insufficient secondary evidence found)	
Commercial / Open source solutions	Gibson et al (2018) describe the open-source NiftyNet platform. Because medical image analysis poses unique challenges for deep learning (variation in data availability, dimensions/size, formatting) NiftyNet provides a high-level deep learning pipeline with components optimized for medical imaging applications (data loading, sampling and augmentation, networks, loss functions, evaluations, and a model zoo). NiftyNet comprises an implementation of the common infrastructure and common networks used in medical imaging, a database of pre-trained networks for specific applications and tools to facilitate the adaptation of deep learning research to new clinical applications with a shallow learning curve. Three illustrative medical image analysis applications built using NiftyNet infrastruc- ture: (1) segmentation of multiple abdominal organs from CT; (2) image regression to predict CT attenuation maps from brain MRI; and (3) generation of simulated ultrasound images for specified anatomical poses. Future applications under development include image classification, registration, and enhancement (e.g. super-resolution) as well as pathology detection. https://www.sciencedirect.com/science/article/pii/S0169260717311823 Yang et al (2017) describe Quicksilver - a fast, open source deformable image registration method. The proposed approach allows patch-wise prediction, without a substantial decrease in registration accuracy, resulting in fast and accurate deformation prediction. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6036629/ TexRAD uses algorithms to extract and quantify texture features in pre-existing medical images. These texture features have been successfully used to demonstrate diagnostic, prognostic and predictive intelligence in scientific research with particular significance in oncology. TexRAD LUNG is the first clinical application of TexRAD in quantifying texture in PET/CT images to assess complexity of lung tumours. https://fbkmed.com/texrad-landing-2/ DIADEM (Brainminer) is an automated system for analysing MR brain scans, providing the clinician with an easily interpreted report that aids their diagnosis of dementia. It uses a patented machine learning algorithm that identifies 150 separate regions of the brain. It then compares each region to its expected size, based on the patient's age, intercranial volume and other factors. The regions are combined into functional lobes to provide a clinically meaningful summary. Within each lobe the most clinically significant regions are individually reported. DIADEM connects directly to the hospital PACS, automatically detecting new MR scans that are suitable for processing. The report is automatically pushed into the PACS for review. http://www.brainminer.co.uk/products.html Nuance mPower – radiology report database which employs Natural Language Processing algorithms. Greatest utility appears to be for radiologists seeking clinical decision support

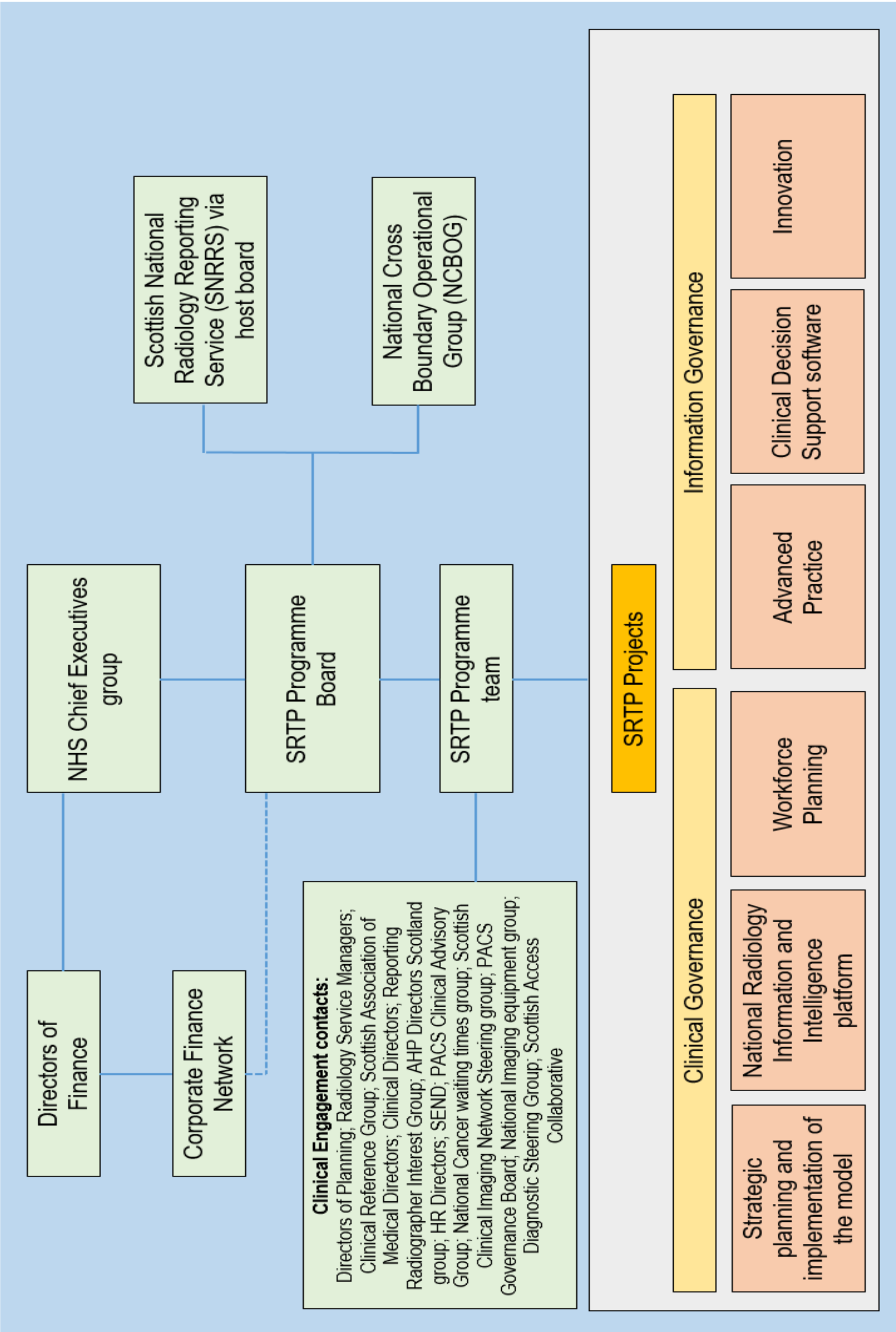
	and follow-up recommendations for complex cases. Currently, mPower algorithms are powered by access to reports from over 500 providers in North America and Europe. Also has ability to monitor compliance by tracking critical results, identify errors/mismatches within reports and radiology department volume-analytics.
Cochrane library ***Check for RCTs in the trials database***	Not relevant
Ongoing secondary research	
EUnetHTA Planned & Ongoing Projects database ***Check for any planned projects by EUnetHTA members on similar topics. You will need to register for an EUnetHTA login to access this resource.***	None
PROSPERO database ***Check for recent systematic review protocols.***	Not relevant
Ongoing research (only if insufficient secondary evidence and primary studies found)	
Various	*Industrial Centre for Artificial Intelligence Research in Digital Diagnostics (iCAIRD):* A pan-Scotland consortium of 13 partners from across academia, the NHS, and industry. iCAIRD's medical imaging research will include developing solutions for more rapid treatment for stroke, expert chest x-ray reading, and partly automated mammogram

Sources	analysis for breast cancer screening. The centre will also carry out digital pathology research to achieve rapid and more accurate diagnosis in gynaecological disease and colon cancer. Limited information available on the nature of research in progress and phase of development. http://www.sinapse.ac.uk/ *DeepLesion* is a NIH Clinical Centre hosted dataset of more than 32,000 medical images, large enough for scientists to train a deep learning neural network and create a large-scale lesion detector with one unified framework. DeepLesion is unlike most lesion medical image datasets currently available, which can only detect one type of lesion. The database has great diversity – it contains all kinds of critical radiology findings from across the body, such as lung nodules, liver tumors, enlarged lymph nodes, and so on. https://nihcc.box.com/v/DeepLesion *MALIBO* - Development and evaluation of machine learning methods in whole body MRI with diffusion weighted imaging for staging of patients with cancer (MAchine Learning In whole Body Oncology). Phase 1: Development of ML pipeline 'A' for automatic anatomic labeling in WB-DW-MR of 50 healthy volunteers using segmentation techniques. Phase 2 training: 150 scans from NIHR STREAMLINE (colorectal/lung cancer, CRUK MELT (lymphoma)& MASTER (lymphoma/prostate cancer) main studies with established disease stage will be used to train machine learned detection of metastases. Interim sensitivity tested in 40-50 scans. Phase 3 validation: 217 scans from the primary studies will be read by radiologists with +ML 'C' using sequential viewing of sequences; internal pilot in first 50-70. DA will be measured against the main study reference standards and RT +/- ML will be recorded. http://wp.doc.ic.ac.uk/bglocker/grant/malibo-machine-learning-in-whole-body-oncology/ https://www.sciencedirect.com/science/article/pii/S0009926019300741?via%3Dihub *MALIMAR* - Development of machine learning support for reading whole body diffusion weighted magnetic resonance imaging (WB-MRI) in myeloma for the detection and quantification of the extent of disease before and after treatment (MAchine Learning In MyelomA Response). Phase 1 (training): WB-MRI scans from a cohort of 160 myeloma patients (120 with active disease) from a single centre and 40 age-relevant healthy volunteers (HV) will be used to develop a ML detection tool to recognise active myeloma. Phase 2 (validation): Sensitivity and RT assessment using WB-MRI -/+ ML in 203 active myeloma 100 inactive myeloma and 50 HV.Phase 3 (disease quantity): A ML quantification tool will be developed then tested on WB-MRI of 60 patients having scans before and after myeloma treatment on iTIMM trial. Quantification score RT and categorisation of response will be assessed +/- ML https://www.fundingawards.nihr.ac.uk/award/16/68/34

Date of search:

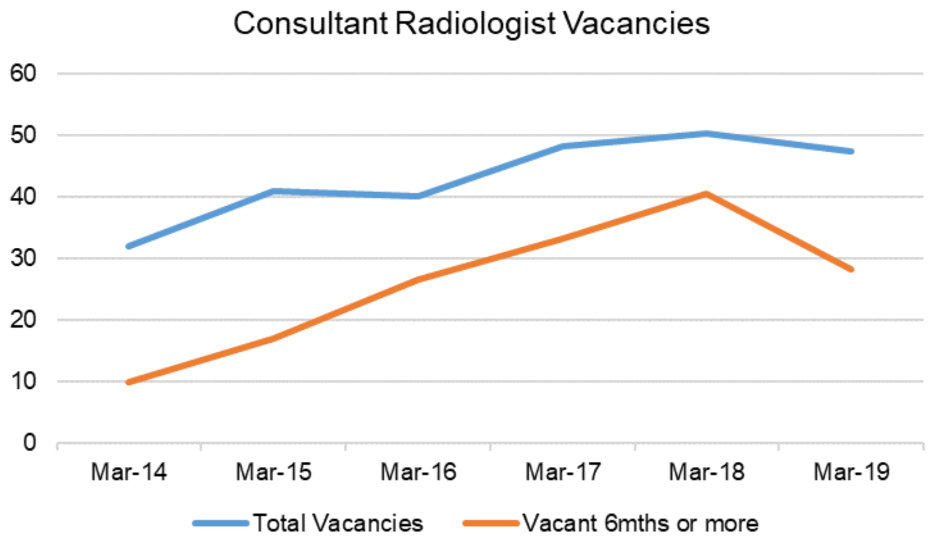
Concepts used:

Appendix 3. SRTP Governance structure

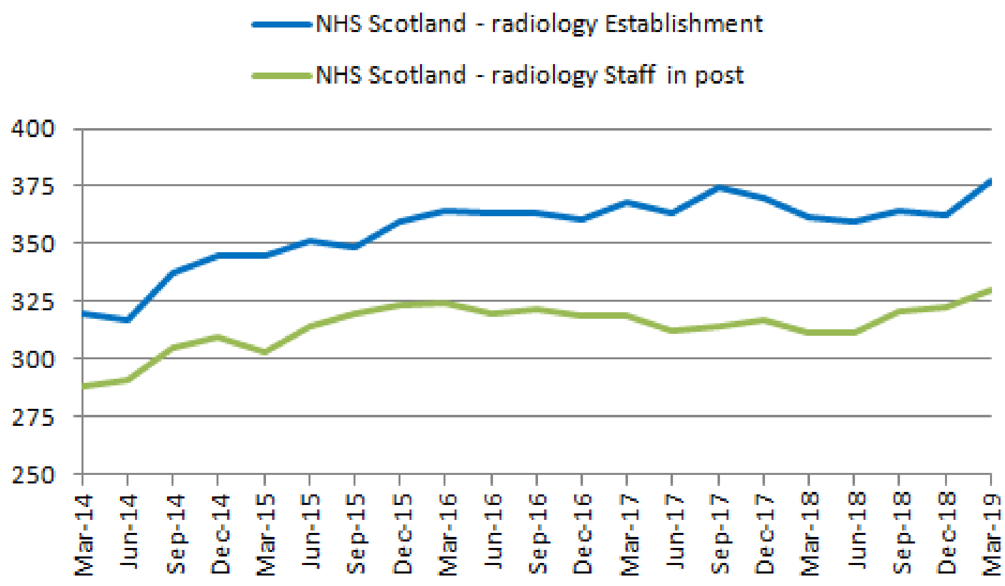


Appendix 4. Consultants in Scotland

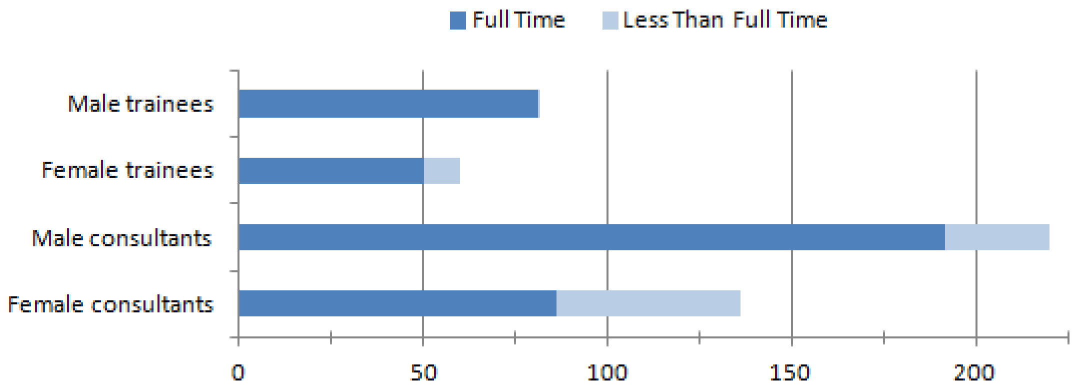
Consultant Radiologist Vacancies



WTE radiology staff in post against establishment for the service



Headcount of staff, by gender, in full time or Less Than Full Time role:



Radiology is a consultant led service, there are no Foundation Year doctors within the service.

RCR analysis of specialist training in Scotland

Forecast flow of trainees starting between 2013-15 (averages):

↓21 doctors per year started specialist training in radiology
↓19 doctors are forecast to complete training and gain CCT
↓12 (64%) are expected to be appointed to consultant clinical radiology posts in Scotland
↓11 whole time equivalent posts are filled after some then choose to work less than full time.

The wte of 11 posts are filled from 21 wte starting specialist training, 53% conversation rate

SG Health Workforce/NES Medical Specialty profiles

Future supply/demand forecasting for radiology, Retirement Projections 2017-2027 and expected CCT output.

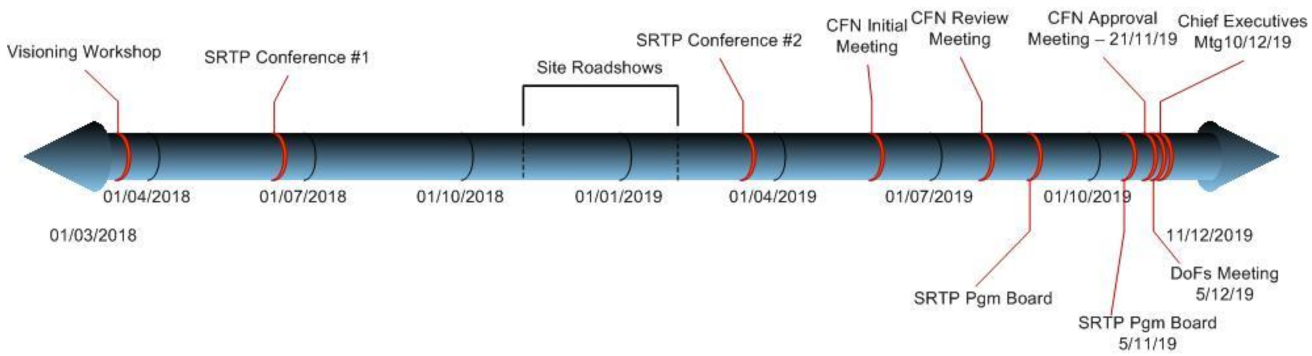
Year	Number of consultants reaching age 61	Estimated CCT output *
2017	10	27
2018	9	21
2019	12	21
2020	6	29
2021	13	27
2022	9.4	26
2023	15	26
2024	9	30
2025	9	30
2026	12	30
2027	9	30
2028	11	30

* based on 6 year average length of training and establishment of 129 (at all stages of training) growing by 10 trainees per year for 5 years from 2018 by expansion at ST 1

This does not account for current consultants taking up new LTFT contracts.

Appendix 5. Service engagement

Figure 10: Key engagement milestones in Phase 1



Beyond these major events and engagement milestones the SRTP Leadership Team has attended national executive groups such as:

- Nurse Directors
- Medical Directors
- Directors of Planning
- Regional Implementation leads
- Scottish Government
- Chief Executives

Individual contact has been maintained between the SRTP Medical Director and individual board clinical leads and also between the Phase 1 Programme Director and executive leads at local, regional and national levels. Various projects have been developed from these interactions and are examined in the Economic Case.

Appendix 6. Options Appraisal

At the second SRTP Conference by asking delegates to choose the highest priorities for transformation in Radiology in facilitated sessions. Other projects were considered but were not prioritised for inclusion during consultation for this phase. The table below refers.

Project options	Scoring	Rank	Recommendation
National Clinical Decision Support Software	49	1	Continue in Phase 2
Advanced Practice	45	2	Continue in Phase 2
Radiology Reporting Bank	36	3	Continue in Phase 2
Radiology Reporting Service	23	4	Continue in Phase 2
Artificial Intelligence Scoping & Pilots	14	5	Phase 2 new project
Radiology Information & Intelligence Service	13	6	Continue in Phase 2
National Reporting IT Platform	9	7	No action - complete
Speciality Reporting Networks	8	9	Not prioritised now
Academy Model	8	9	Not prioritised now
Consultant Radiologist Job Design	7	11	No action - complete
PACS Re-procurement	6	12	Underway (NSS)
Radiology Out of Hours Reporting Service	4	13	Not prioritised now
Recruitment & Matching	4	13	Not prioritised now
National Vetting IT Platform	3	15	Not prioritised now

Appendix 7. Option 2 – Project scope

Scottish Radiology Reporting Service Solutions

A national bank model for Radiologists to perform additional sessions has been established to pool resource and act as a mechanism to manage workflow and pay for additional Radiologist sessions in a standard way. This will take the form of a virtual hub (SNRRS Bank), to be hosted by Golden Jubilee National Hospital, enabling Radiologists to volunteer for additional sessions paid using the newly agreed national consultant rate. The pilot will start in Q3 2019 and is scheduled to run for 12 months.

Stakeholders indicated that home working and additional workstations would be central to implementing cross boundary reporting. Phase 1 of the SRTP has therefore established a contract to access fifty workstations for use across Scotland and ran a small pilot to consider the implications of more widespread home working utilising the new IT connectivity and these additional workstations.

The above pilots, along with previous work in Phase 1, will provide the evidence and safe working environment which will allow a national cross boundary reporting service to be established as business as usual. The proposed service will be more cost-effective than the current private-sector outsourcing model that all Boards employ and have the advantage of providing an alternative method of managing backlogs of image reporting within the NHS.

Advanced Practice

Advanced Practice (AP) in Radiography was identified as a priority piece of work from stakeholder engagement. Phase 1 has successfully proven a model of cross boundary reporting by Radiographers. The AP project has worked closely with the Scottish Access Collaborative on Radiographer AP in breast pathways and with the Scottish Clinical Imaging Network (SCIN) on this and other aspects of developing the AP workforce. In addition, Phase 1 has begun to scope the Sonographer workforce.

There are a number of possible AP roles which could support establishment of a sustainable multidisciplinary workforce. These are currently developed across some NHS boards however in a limited way which at times doesn't fully maximise benefits. There is significant interest in a national approach to assessing need, training and then employing staff in different ways to maximise AP skill sets.

This business case proposes projects around Radiographer Reporting, Sonography and scoping the potential for other roles as part of strategic workforce planning. Continuing to work alongside the Scottish Clinical Imaging Network and initiatives such as the Scottish Access Collaborative, to assess need across Scotland, Phase 2 will seek innovative ways to increase overall capacity and evolve the workforce to suit changing need within the service.

Workforce Planning

The availability of systematic and standardised service data allows for more robust workforce planning across the Radiology system in Scotland. The enduring problem of matching workforce capacity to service demand relies on up to date service data. Monitoring activity and workforce trends alongside service developments, provides the ability to model future workforce needs and inform training schemes (Radiologists and Radiographers) and recruitment / employment models.

This business case proposes further development of an existing workforce modelling tool and establishing a small team to support this planning work on an ongoing basis.

National Radiology Information and Intelligence Platform (NRIIP)

Our stakeholders worked to define and agree a national data set and definitions. This data is now stored in the National Radiology Information and Intelligence Platform (NRIIP) within the National Services Scotland (NSS) Corporate Data Warehouse (CDW) and will facilitate the ability to collate, analyse and share national radiology data through the National Radiology Dashboards. This will enable local, regional and national service planning and improvement.

Stakeholders have identified opportunities to expand the breadth of indicators and analytical tools available through the dashboards, which will allow more meaningful analysis of activity by comparing with workforce, acquisition capacity and other relevant indicators. This business case proposes building on work already done to better serve the needs of local service and strategic planning.

Clinical Decision Support (CDS)

Phase 1 of the SRTP has explored the technical and operational feasibility of implementing existing Clinical Decision Support software. A pilot project has been agreed which will use an off the shelf product and test use out in two NHS Boards over a period of a year (2020/21). The project will assess the impact on demand, of providing this type of support, to referring clinicians.

This business case proposes support for that pilot during 2020/21 and also scoping work to assess implementation of CDS across Scotland, beyond the pilot. A further business case will be required to support national implementation given the significant unknowns in terms of products available at that time and benefits from investment.

Artificial Intelligence (AI)

Interest in AI has grown over recent years, with professionals and vendors both keen to develop and test technology across a range of areas. In Radiology there are a number of potential uses of AI and some are already being tested under systematic conditions as part of initiatives in Mammography and Stroke etc. Early work by the Scottish Health Technologies Group (SHTG) commissioned during Phase 1, indicates the different functions and range of potential uses in Radiology.

There is a growing need to assess priorities and plan activity in this area if duplication of effort is to be avoided and maximum benefit realised for NHS Scotland. Given the potential for AI to support Radiology services over the coming years it will become more important to understand the likely impact and build that into planning work going forward.

This business case proposes a collaborative approach to scoping and planning AI over the coming years, allowing service priorities to drive investment and further activity. It also proposes working closely with countries across the UK, who all face the same lack of capacity and are similarly keen to assess AI potential.

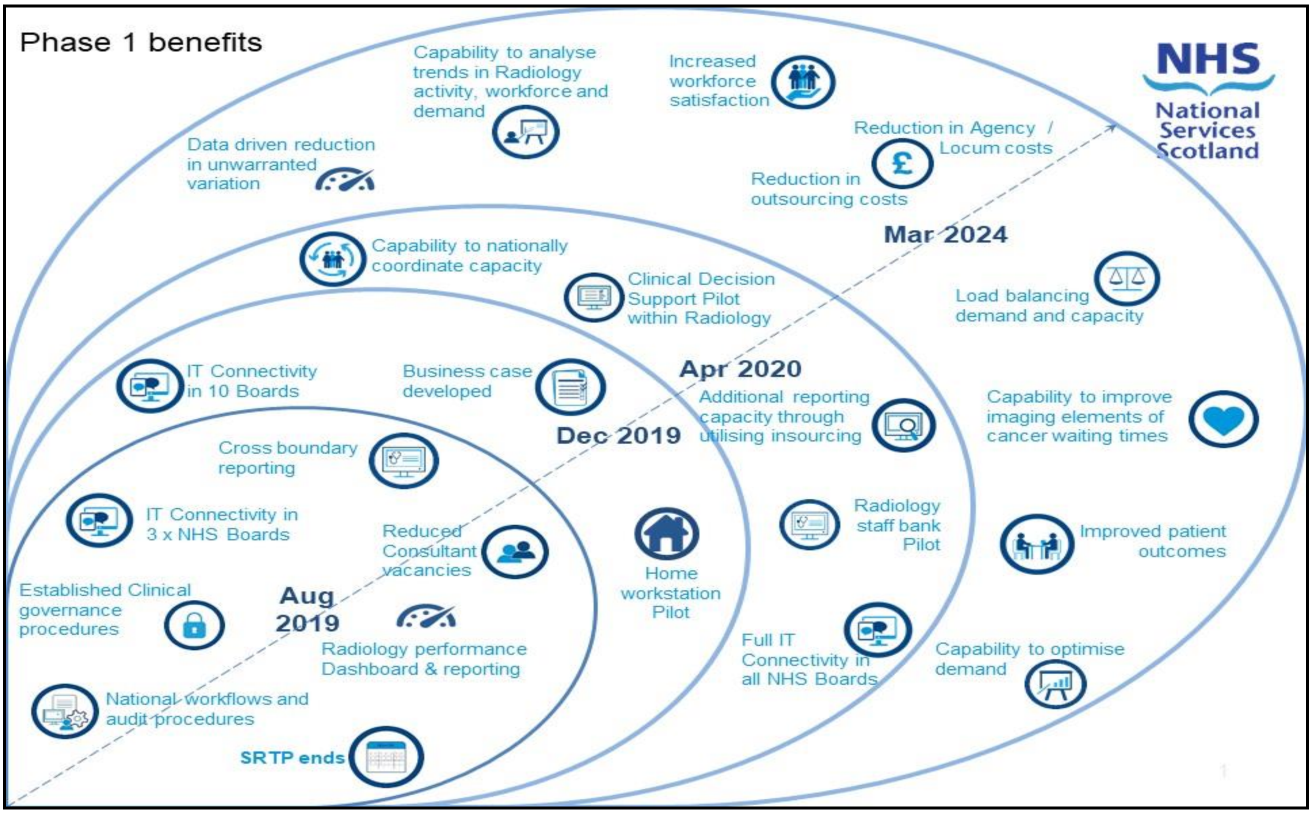
Appendix 8. Benefits from SRTP Phase 1 Business Case

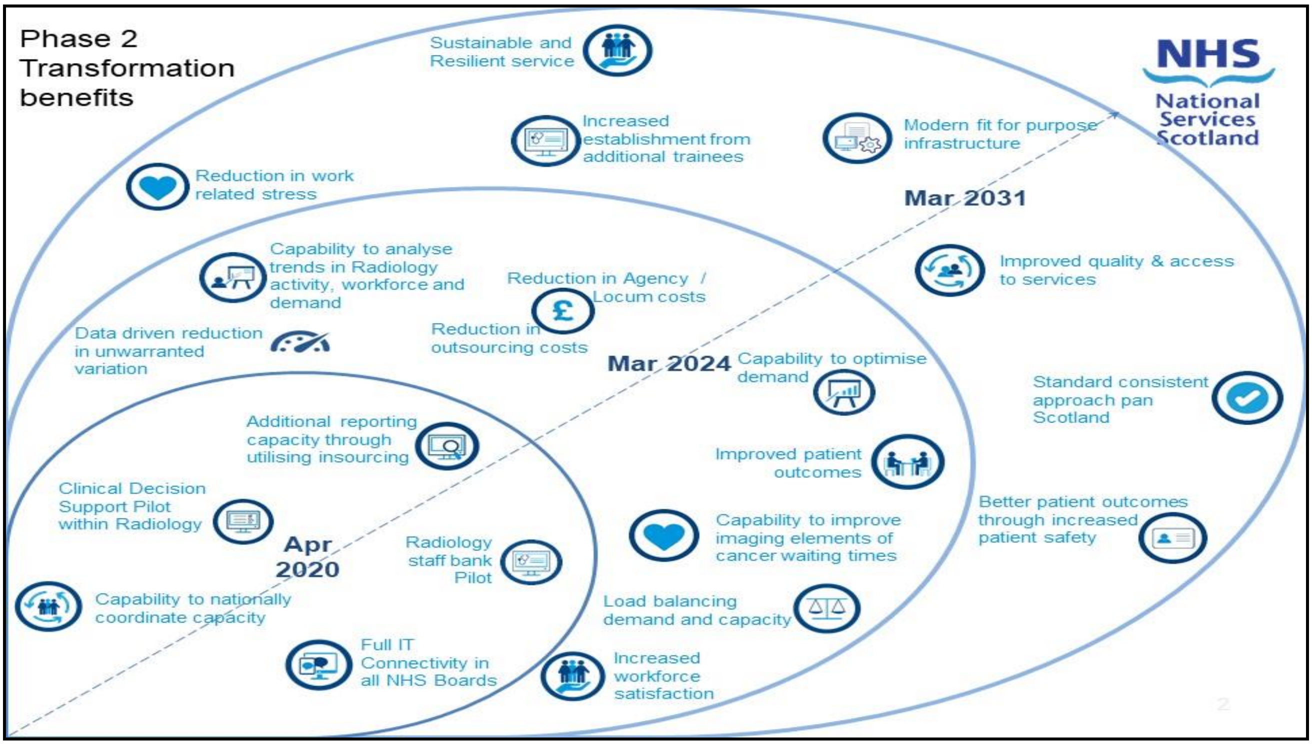
As a reminder, the following benefits (Table 1) were defined in the first SRTP business case.

Table 16: Benefits Realisation Matrix, Section F, p56 of 2017 SRTP business case

Benefit	Anticipated Measure	Anticipated Timescale
Net Financial Benefit	£1.5m per annum	2018/19 onwards
Reduction in overall costs of image reporting including outsourcing costs	£4.5m per annum	2020/21 onwards
Increased productivity due to improved IT	1% productivity gain £0.9m per annum	2018/19 onwards
Improved strategic planning	Demand and capacity planning via NRIIP	2018/19 onwards
Optimisation of workforce	Increased Reporting Capacity	2018/19 onwards
Service sustainability	Patient Access Targets	2018/19 onwards
Service improvement	Via NRIIP	2018/19 onwards

Appendix 9. Benefits Roadmap





Appendix 10. Assumptions

Area	Source of data	Forecast assumption
Assumptions for financial modelling		
Outsourcing spend	NSS Procurement Outsourcing costs 2018	Assumed if no increase in demand, outsourcing costs remain flat
Insourcing / Locum spend	Royal College of Radiologists (RCR)- Workforce Census Report 2018	Assumed if no increase in demand, insourcing/locum costs remain flat
Clinical / Medical spend	15% uplift applied to 2015/16 Boards data *CFN members were asked to provide 2018/19 data, 3 of the 6 boards returned increases between 12-17%. These 3 boards represent 47% of NHS Scotland in terms of volume and spend	GEM assumed these costs would not be impacted by the project
Growth in demand -Outsourcing -Insourcing / locums -Substantive staff	Average annual increase based on historical trends 2012-2018 from Cost Book	Assumption made that 50% of annual increase could be completed by additional staff and resulting 50% of exams will be split between outsourcing and insourcing/locums. Assumption that consultants can complete 4 CTs or 4 MRIs or 20 plain films per hour Assumed a consultant radiologist works **40 hrs/week for 42 weeks** (i.e. annual leave, sick leave, study leave excluded). Assumed growth increases by the same number of exams each year, i.e. Y0 = x, Y1 = 2x, Y2 = Y1+x, Y3 = Y2+x, etc
Equipment - non capital	15% uplift applied to 2015/16 Boards data	Same costs factored in across all options

	*re CFN member returns described above	
Gross Pay - Substantive	4% uplift applied to 2015/16 Boards data	From 19/20 assumed 1% pay uplift YOY to account for inflation
Gross Pay - non substantive	47% reduction applied to 2015/16 Boards data 4 CFN Board members submitted updated non pay data for 2018/19, 47% reduction is the average of the 4 Boards. These 4 Boards represent 60% of NHS Scotland in terms of volume and spend	From 19/20 assumed 1% pay uplift YOY to account for inflation
Implementation Costs	Developed by the SRTP team for the business case.	Assumes a programme team for 3 years and BAU continuing for 10 years. NSS day rates 1819 used to calculate costs. No overhead recovery has been applied. 3% increase YOY included for Y2 and Y3
Cost of doing nothing	Calculation	Assumed this is the total cost of annual additional demand plus current spend on outsourcing, insourcing/locums
General assumption – options 1-3 Cost per outsourced exam Net saving based on realistic recruitment Annual savings CT– cost of outsourced exam v SNRRS Bank	NSS Procurement Outsourcing Rates Calculation Calculation: outsourced cost of CT minus derived cost of CT through the SNRRS Bank	Average cost taken across all suppliers for each modality (CT/MR/PF). Assumed that cost per exam would remain fixed. Assumed that net savings will be the result of all activity done to avoid outsourcing as described below but net recruitment will be newly qualified consultants - retirees Assumed in-sourcing hourly rate through new SNRRS Bank as the new Consultant Bank Rate plus on costs Assumed productivity rate for CT same as above. Used this to determine effective cost per CT through new SNRRS Bank.

Amount of reporting time new staff will report for each week		Assumed new staff will report for 80% of time on the basis that the reporting work will be spread across the department
Option 1 – Do minimum **Capacity** CTs from SNRRS Bank Pilot Consultants hired for additional CT demand **Savings** **CT savings** **MR and PF savings**	 Calculation Calculation – difference between outsourcing cost and effect cost of the SNRRS Bank, insourcing/locum and hiring additional staff Calculation – difference between outsourcing cost and hiring new staff to meet the demand	 Assumed that for the SNRRS pilot, 30 consultants will sign up and each work on average 4hrs/week over 42 weeks. As above, assumed 4 CTs can be completed per hour Assumed 2 x consultants hired to work on demand increase for CTs Assumed that as CTs are the most expensive exam to outsource that these will be the priority to in-source through the SNRRS Bank Assumed that savings are a sum of these calculations Assumed that the number of new staff hired will align with the newly qualified Radiologists (CCT) – Retirees This has been named realistic recruitment
Option 2 and Option 3 – assumptions same for both **Capacity** CTs from SNRRS Bank (extended from pilot) Capacity from Retirees Capacity from Radiographers	 Calculation from boards bespoke data capture for Business Case 1 Data based on figures from Scottish Government regarding retiring radiologists Calculation	 Assumed that 50% of radiologists working less than 11PAs /week will increased to 11PAs/ week over a 42 week year and this additional work will be done for the SNRRS Bank. Assumption that 50% of retirees will choose to work on average 2 PAs/week over 42 weeks. Assumed a retiree will work for 2 years on the bank. Assumed that reporting

Consultants hired for additional CT demand **Savings** CT savings MR and PF savings	As option 1 As option 1	radiographers can report 20% of all Plain Film demand at a rate of 17 per hour Assumed that time freed up from radiologists reporting Plain Films will be used for CTs

Appendix 11. Implementation Team

Detailed programme team structure for each option:

Option 0

No associated implementation team

Option 1

				Year 1	Year 2	Year 3
	Project	**Role**	**Staff grade**	**WTE**	**WTE**	**WTE**
SRTP Phase 2 Implementation Programme Team	**SNRRS Year 1 Pilot Support & Development**	Workflow Manager	7	3.0	1.0	1.0
		Workflow Administrators	5	1.0	1.0	1.0
		Project Manager	7	1.0	0.0	0.0
		Project Support Officer	5	0.5	0.0	0.0
Business As Usual Phase 2	**SNRRS**	Medical Director / Clinical Lead	Consultan	0.4	0.4	0.4
		Workflow Manager	7	-	2.0	2.0
		Workflow Administrators	5	-	1.0	1.0
	Data collection and analysis	Analytics & Intelligence	Various	Various	Various	Various
		Data Management	Various	Various	Various	Various
		Digital and Security	Various	Various	Various	Various
	IT	Contract and Service Management	Various	0.4	0.4	0.4
		IT Project Change	Various	Various		

Option 2

				Year 1	Year 2	Year 3
	Project	**Role**	**Staff grade**	**WTE**	**WTE**	**WTE**
SRTP Phase 2 Implementation Programme Team	**Programme Support Team**	Medical Director / Clinical Lead	Consultan	0.4	0.4	0.4
		Programme Director	8c	1.0	1.0	1.0
		Programme Manager	8a	1.0	1.0	1.0
		Project Support Officer	5	2.0	2.0	2.0
	SNRRS Year 1 Pilot Support & Development	Workflow Manager	7	3.0	1.0	1.0
		Workflow Administrators	5	1.0	1.0	1.0
		Project Manager	7	1.0	-	-
	Workforce Planning	HR / Workforce Lead	7	1.0	1.0	0.0
		Project Manager	7	0.5	0.5	0.5
	Clinical Decision Support	Clinical Lead	Consultan	0.1	0.2	0.2
		Project Manager	7	0.5	1.0	1.0
	Advanced Practice	Clinical Lead	Consultan	0.2	0.2	0.2
		Project Manager	7	1.0	1.0	1.0
		Radiographer Lead	8b	0.6	0.6	0.6
		Sonographer Lead	7	0.2	0.2	0.2
		Radiographer	7	0.2	0.2	0.2
	Artificial Intelligence	Project Manager	7	0.5	0.5	0.5
		Clinical Lead	Consultan	0.1	0.2	0.2
	NSS PHI / BI Team	Analytical & Intelligence	Various	Various	Various	Various
		Data Management	Various	Various	Various	Various
		Digital and Security	Various	Various	Various	Various
Business As Usual Phase 2	**BAU Leadership and Managment**	Medical Director / Clinical Lead	Consultan	0.2	0.2	0.2
		Exec Lead	Exec	-	-	0.4
	SNRRS	Workflow Manager	7	-	2.0	2.0
		Workflow Administrators	5	-	1.0	1.0
		Service Manager support to SNRRS	8b	0.4	0.4	0.4
	Data collection and analysis	Analytics & Intelligence	Various	Various	Various	Various
		Data Management	Various	Various	Various	Various
		Digital and Security	Various	Various	Various	Various
	IT	Contract and Service Management	Various	0.4	0.4	0.4
		IT Project Change	Various	Various	-	-

OPTION 3

				Year 1	Year 2	Year 3
	Project	**Role**	**Staff grade**	**WTE**	**WTE**	**WTE**
SRTP Phase 2 Implementation Programme Team	**Strategic Development**	Change Management / OD	7	0.5	0.5	0.5
		Clinical Leadership Fellow	Registrar	0.5	0.5	0.5
		Health Economist	8a	0.5	0.5	0.5
		Business Case Development	7	0.5	0.5	0.5
		Consultation / Events Management /	5	1.0	1.0	1.0
	Programme Support Team	Medical Director / Clinical Lead	Consultan	0.4	0.4	0.4
		National Exec Lead	Exec E	0.4	0.4	0.4
		Programme Manager	8b	1.0	1.0	1.0
		Project Manager	7	-	1.0	1.0
		Analyst	6	1.5	1.5	1.5
		Project Support Officer	5	2.0	2.0	2.0
	SNRRS Year 1 Pilot Support & Development	Workflow Manager	7	3.0	1.0	1.0
		Workflow Administrators	5	1.0	1.0	1.0
		Project Manager	7	1.0	-	-
		Project Support Officer	5	1.0	1.0	1.0
	Workforce Planning	HR / Workforce Lead	7	1.0	1.0	0.0
		Project Manager	7	0.5	0.5	0.5
	Clinical Decision Support	Clinical Lead	Consultan	0.2	0.2	0.2
		Project Manager	7	0.5	1.0	1.0
	Advanced Practice	Clinical Lead	Consultan	0.2	0.2	0.2
		Project Manager	7	1.0	1.0	1.0
		Radiographer Lead	8b	0.6	0.6	0.6
		Sonographer Lead	7	0.2	0.2	0.2
		Radiographer	7	0.2	0.2	0.2
	Artificial Intelligence	Clinical Lead	Consultan	0.2	0.2	0.2
		Project Manager	7	0.5	0.5	0.5
	NSS PHI / BI Team	Analytical & Intelligence	Various	-	1.5	1.5
		Data Management	Various	-	0.8	0.8
		Digital and Security	Various	-	0.2	0.2
Business As Usual Phase 2	**BAU Leadership and Managment**	Medical Director / Clinical Lead	Consultan	0.6	0.6	0.6
		Regional Clinical Lead	Consultan	1.5	1.5	1.5
		National Exec Lead	Exec E	0.6	0.6	0.6
		Regional Exec Lead	Exec D	3.0	3.0	3.0
		Service Planning Lead	8a	1.0	1.0	1.0
		Recruitment Lead	7	1.0	1.0	1.0
		Radiologist Training & Co-ordination	Consultan	0.5	0.5	0.5
		Radiographer Training & Co-ordinatio	8b	0.5	0.5	0.5
		Digital Innovation Lead (Clinical Fello	Registrar	0.4	0.4	0.4
	SNRRS	Workflow Manager	7	-	2.0	2.0
		Workflow Administrators	5	-	1.0	1.0
		Service Manager support to SNRRS	8b	-	0.4	0.4
	Data collection and analysis	Analytics & Intelligence	Various	Various	Various	Various
		Data Management	Various	Various	Various	Various
		Digital and Security	Various	Various	Various	Various
	IT	Contract and Service Management	Various	0.4	0.4	0.4
		IT Project Change	Various	Various	-	-

Appendix 12. Non-Monetary Benefits criteria and weighting

The criteria are listed below, along with a weighting assigned as to their relative importance as defined by the clinical and service need.

- Sustainable and resilient service – improved efficiencies (Weighting: 30%)
    - Increased resilience of radiology service at a local level (e.g. ability to deal with local capacity shortfalls)
    - A resilient and flexible radiology service that can respond to challenges around capacity and demand via a collegiate approach
    - Support for clinical services in acute and primary care
    - Support emergency and unscheduled care
    - Support remote and rural NHS Boards
    - Supports improved workflow and increased productivity
    - Maximisation of role utilisation and flexibility
    - Ability to create reporting work lists and allocate reporting across Health Board boundaries
    - Ability to operationally manage and strategically plan services utilising NHS datamarts;
    - Ability to model future services, utilising NSS data marts

- Improved quality and access to services (Weighting: 30%)
    - Maintain local image acquisition and therefore local patient access
    - Retain Radiologists at local level
    - Reduce the clinical risks associated with outsourcing, locum and agency staff
    - Allow improved expert Radiology input to Multi-Disciplinary Team meetings leading to improved diagnosis, staging and treatment plans for patients including cancer patients
    - Allow more effective use of the expert skills of the radiology workforce
    - Support cross-boundary image reporting
    - Allow cross-boundary specialist opinion
    - Improve patient experience by expediting diagnosis and treatment

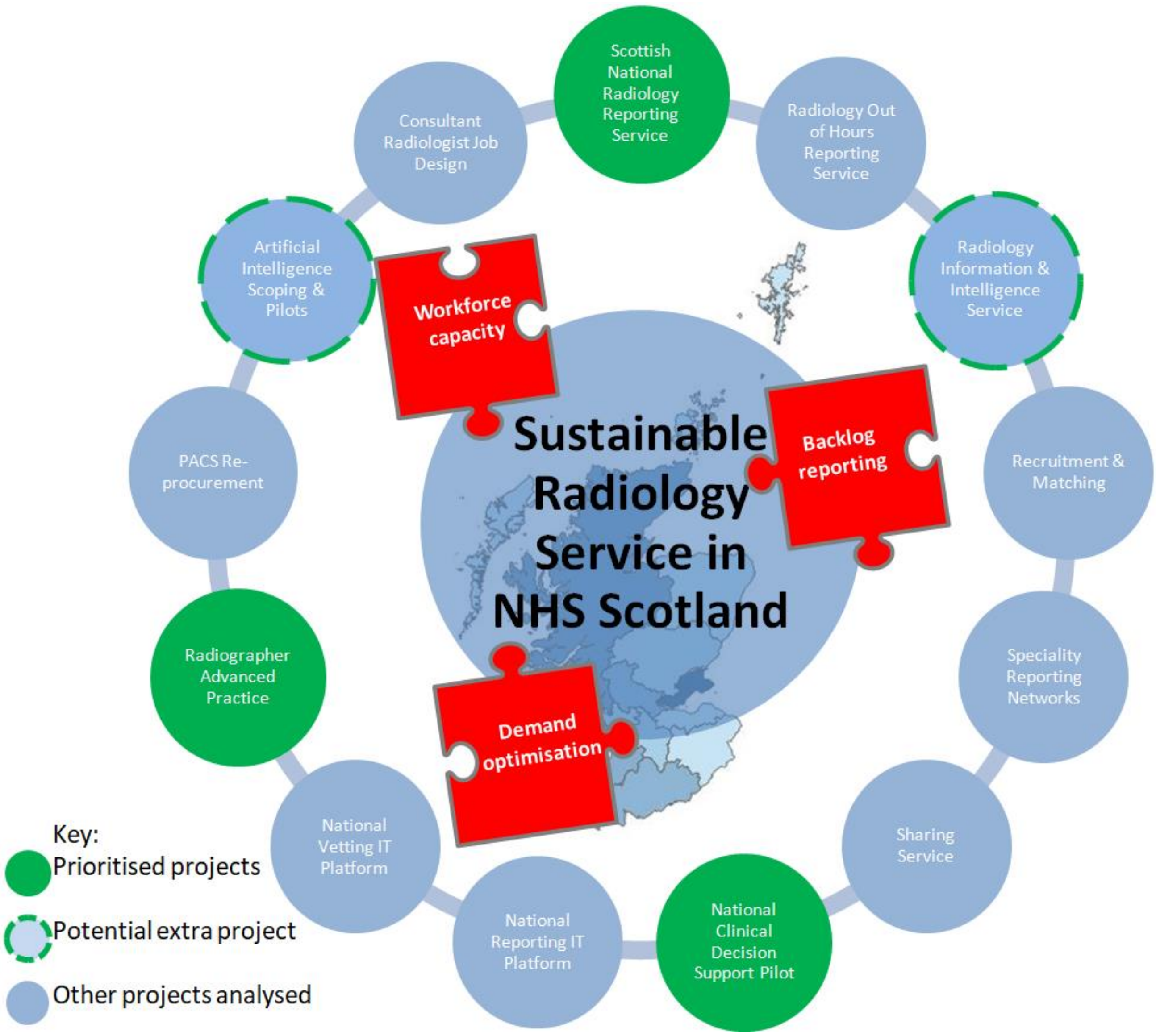
- Standardised consistent approach pan Scotland (Weighting: 18%)
    - Reduce unwarranted variation in demand for radiology services
    - Reduce unwarranted variation in radiology practice.

- Improved wellbeing of staff (Weighting 10%)
    - Recruitment and retention of staff

- Increased job satisfaction; and
- Reduction in work-related stress.

- Modern fit for purpose infrastructure (Weighting: 12%)
  - Supports requirements of current clinical services;
  - Meets the anticipated needs of future clinical services;
  - Supports linkage to current NSS data marts; and
  - Delivers future flexibility of data analysis according to anticipated service needs.

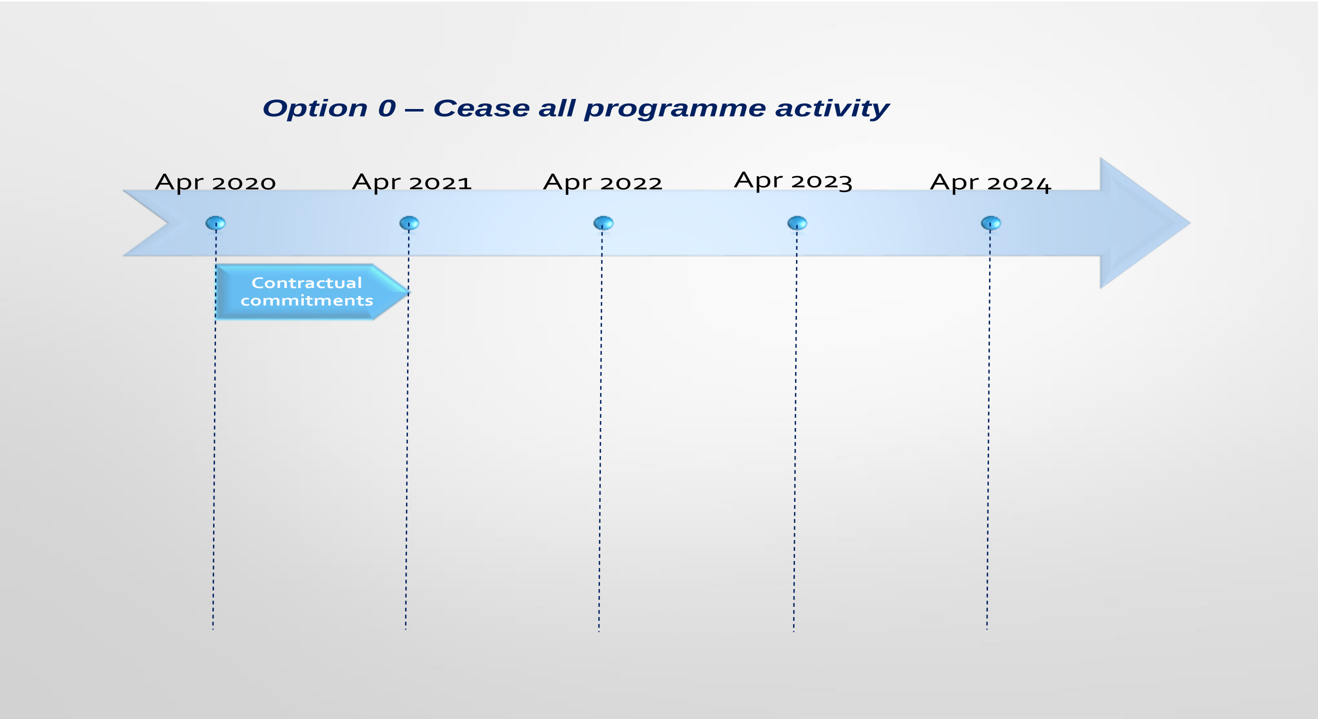
Appendix 13. Future Project options

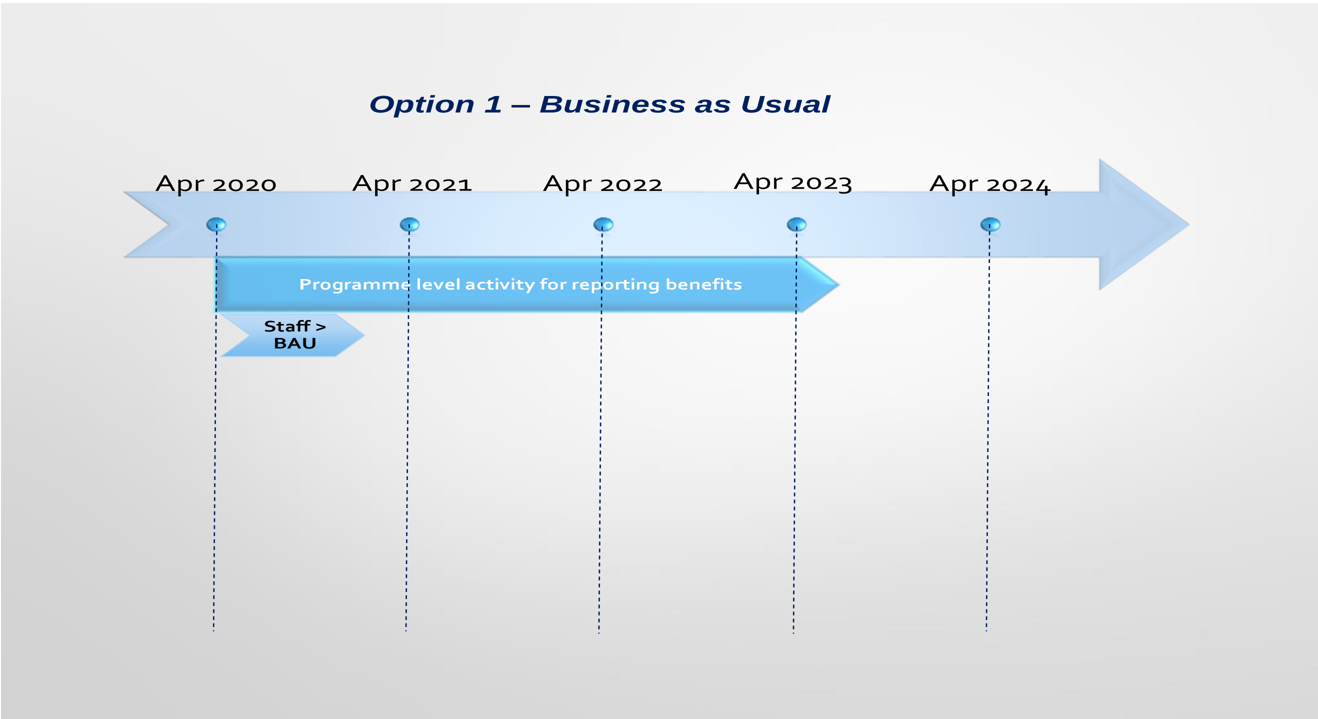


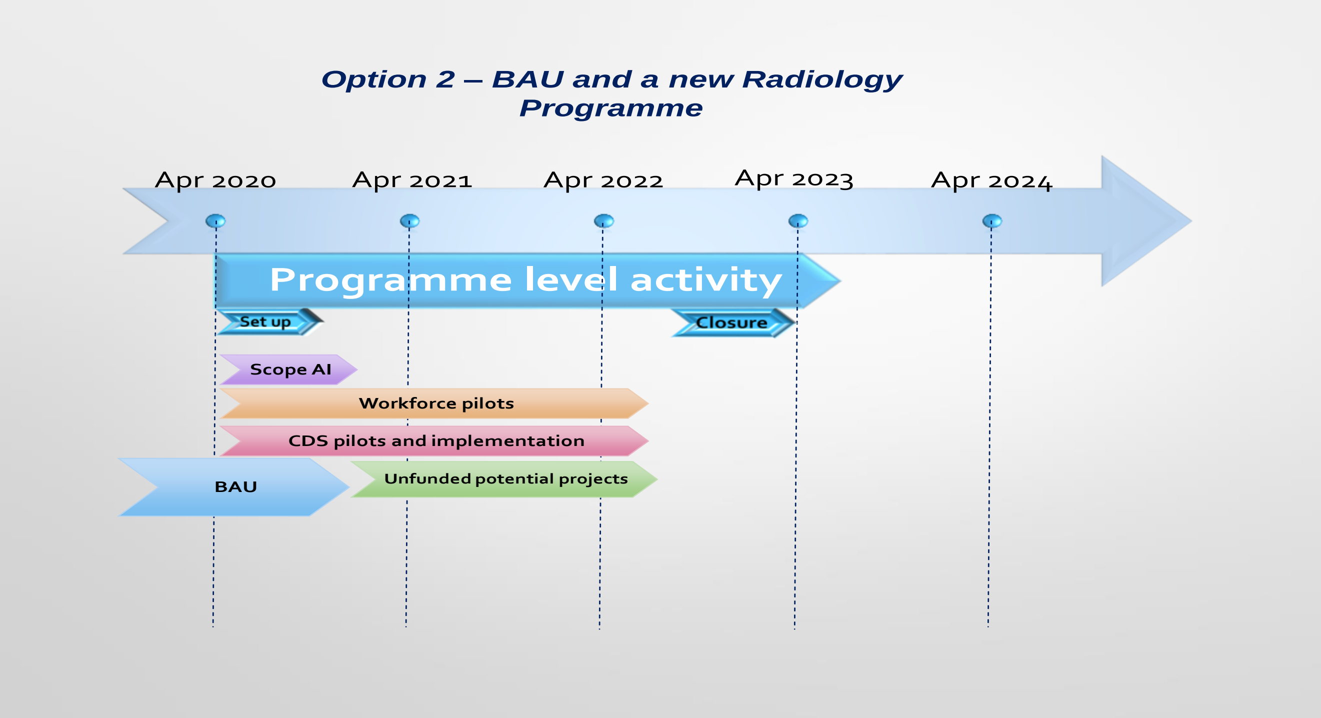
Appendix 14. Financial Model

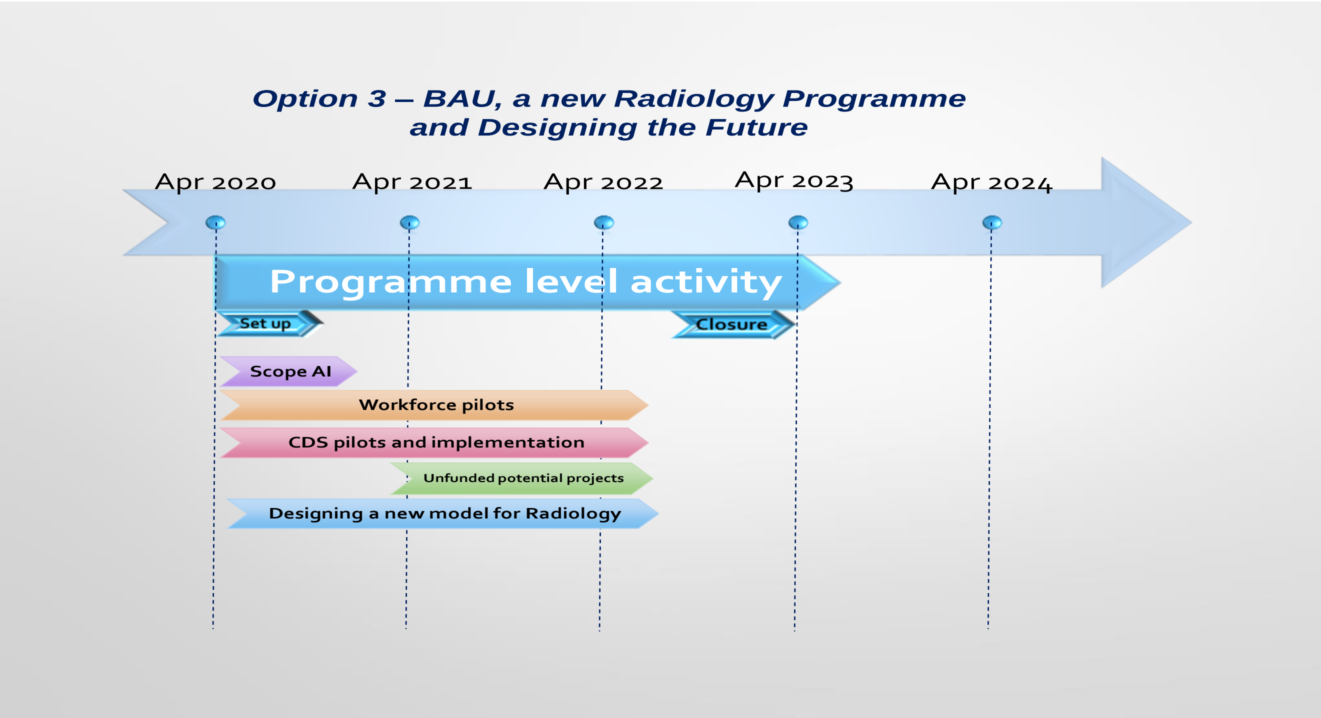
Options Summary - SRTP Business Case Phase 2												
Year	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Total**
Implementation Costs												
Option 0		£ 376,793	£ 384,329	£ 392,015	£ 127,793	£ -	£ -	£ -	£ -	£ -	£ -	**£ 1,280,930**
Option 1 (programme ends after 3 years and only IT/NRIIP/SNRRS costs)		£ 1,038,797	£ 1,006,016	£ 981,278	£ 838,012	£ 838,012	£ 838,012	£ 838,012	£ 838,012	£ 852,997	£ 852,997	**£ 8,922,144**
Option 2 (programme ends after 3 years and only IT/NRIIP/SNRRS costs)		£ 1,670,381	£ 1,849,473	£ 1,837,705	£ 864,012	£ 864,012	£ 864,012	£ 864,012	£ 864,012	£ 864,012	£ 864,012	**£ 11,405,642**
Option 3 (programme ends after 3 years and only IT/NRIIP/SNRRS costs)		£ 2,787,946	£ 3,006,128	£ 2,955,516	£ 1,810,005	£ 1,810,005	£ 1,810,005	£ 1,810,005	£ 1,810,005	£ 1,810,005	£ 1,810,005	**£ 21,419,627**
Option 0 Do nothing												
Growth in Demand												
CT	£713,772	£1,427,544	£2,141,316	£2,855,088	£3,568,860	£4,282,632	£4,996,403	£5,710,175	£6,423,947	£7,137,719	£7,851,491	**£46,395,175**
MR	£354,149	£708,297	£1,062,446	£1,416,595	£1,770,744	£2,124,892	£2,479,041	£2,833,190	£3,187,339	£3,541,487	£3,895,636	**£23,019,668**
PF	£138,988	£277,976	£416,964	£555,951	£694,939	£833,927	£972,915	£1,111,903	£1,250,891	£1,389,879	£1,528,867	**£9,034,211**
Annual additional demand	£1,206,909	£2,413,817	£3,620,726	£4,827,634	£6,034,543	£7,241,451	£8,448,360	£9,655,268	£10,862,177	£12,069,085	£13,275,994	**£78,449,054**
Current outsourcing/insourcing spend	£11,594,046	£11,594,046	£11,594,046	£11,594,046	£11,594,046	£11,594,046	£11,594,046	£11,594,046	£11,594,046	£11,594,046	£11,594,046	**£115,940,460**
Total cost of doing nothing	£12,800,954	£14,007,863	£15,214,772	£16,421,680	£17,628,589	£18,835,497	£20,042,406	£21,249,314	£22,456,223	£23,663,131	£24,870,040	**£194,389,514**
Annual increase in cost of doing nothing		9%	9%	8%	7%	7%	6%	6%	6%	5%	5%	
Cumulative increase in cost of doing nothing		9%	19%	28%	38%	47%	57%	66%	75%	85%	94%	
Option 1												
Net saving assuming recruiting to all posts required		£1,846,582	£1,932,934	£2,015,601	£2,100,725	£2,185,848	£2,269,129	£2,352,410	£2,435,691	£2,518,971	£2,602,252	**£22,260,143**
Net saving based on realistic recruitment		£1,322,553	£692,484	£901,255	£468,884	£1,238,409	£1,228,068	£974,891	£1,209,935	£1,041,683	£1,035,281	**£10,113,443**
Contribution to additional demand		55%	19%	19%	8%	17%	15%	10%	11%	9%	8%	
Contribution to total do nothing demand		9%	5%	5%	3%	7%	6%	5%	5%	4%	4%	
Option 1 - net impact		£283,756	-£313,532	-£80,023	-£369,128	£400,397	£390,057	£136,879	£371,923	£188,686	£182,284	**£1,191,299**
Option 1 - cumulative impact		£283,756	-£29,776	-£109,799	-£478,927	-£78,529	£311,527	£448,406	£820,330	£1,009,015	£1,191,299	
Option 2												
Net saving assuming recruiting to all posts required		£ 1,693,209	£ 1,784,218	£ 1,874,587	£ 2,006,600	£ 2,173,836	£ 2,235,972	£ 2,298,107	£ 2,360,243	£ 2,422,378	£ 2,484,514	**£ 21,333,663**
Net saving based on realistic recruitment		£ 1,349,813	£ 780,050	£ 1,185,524	£ 710,467	£ 2,212,732	£ 2,099,310	£ 1,601,782	£ 1,918,192	£ 1,598,773	£ 1,542,655	**£ 14,999,298**
Contribution to additional demand		56%	22%	25%	12%	31%	25%	17%	18%	13%	12%	
Contribution to total do nothing demand		10%	5%	7%	4%	12%	10%	8%	9%	7%	6%	
Option 2 - net impact		-£320,568	-£1,069,423	-£652,181	-£153,545	£1,348,720	£1,235,298	£737,771	£1,054,180	£734,762	£678,643	**£3,593,657**
Option 2 - cumulative impact		-£320,568	-£1,389,991	-£2,042,172	-£2,195,717	-£846,997	£388,301	£1,126,072	£2,180,252	£2,915,013	£3,593,657	
Option 3												
Net saving assuming recruiting to all posts required		£ 1,697,509	£ 1,812,262	£ 2,049,565	£ 2,111,701	£ 2,173,836	£ 2,235,972	£ 2,298,107	£ 2,360,243	£ 2,422,378	£ 2,484,514	**£ 21,646,085**
Net saving based on realistic recruitment		£ 1,472,690	£ 984,912	£ 1,906,412	£ 907,506	£ 2,212,732	£ 2,099,310	£ 1,601,782	£ 1,918,192	£ 1,598,773	£ 1,542,655	**£ 16,244,965**
Contribution to additional demand		61%	27%	39%	15%	31%	25%	17%	18%	13%	12%	
Contribution to total do nothing demand		11%	6%	12%	5%	12%	10%	8%	9%	7%	6%	
Option 3 - net impact		-£1,315,256	-£2,021,216	-£1,049,104	-£902,499	£402,727	£289,305	-£208,223	£108,187	-£211,232	-£267,350	**-£5,174,662**
Option 3 - cumulative impact		-£1,315,256	-£3,336,472	-£4,385,575	-£5,288,075	-£4,885,348	-£4,596,043	-£4,804,266	-£4,696,079	-£4,907,311	-£5,174,662	

Appendix 15. HIGH LEVEL TIMELINE (PER OPTION)

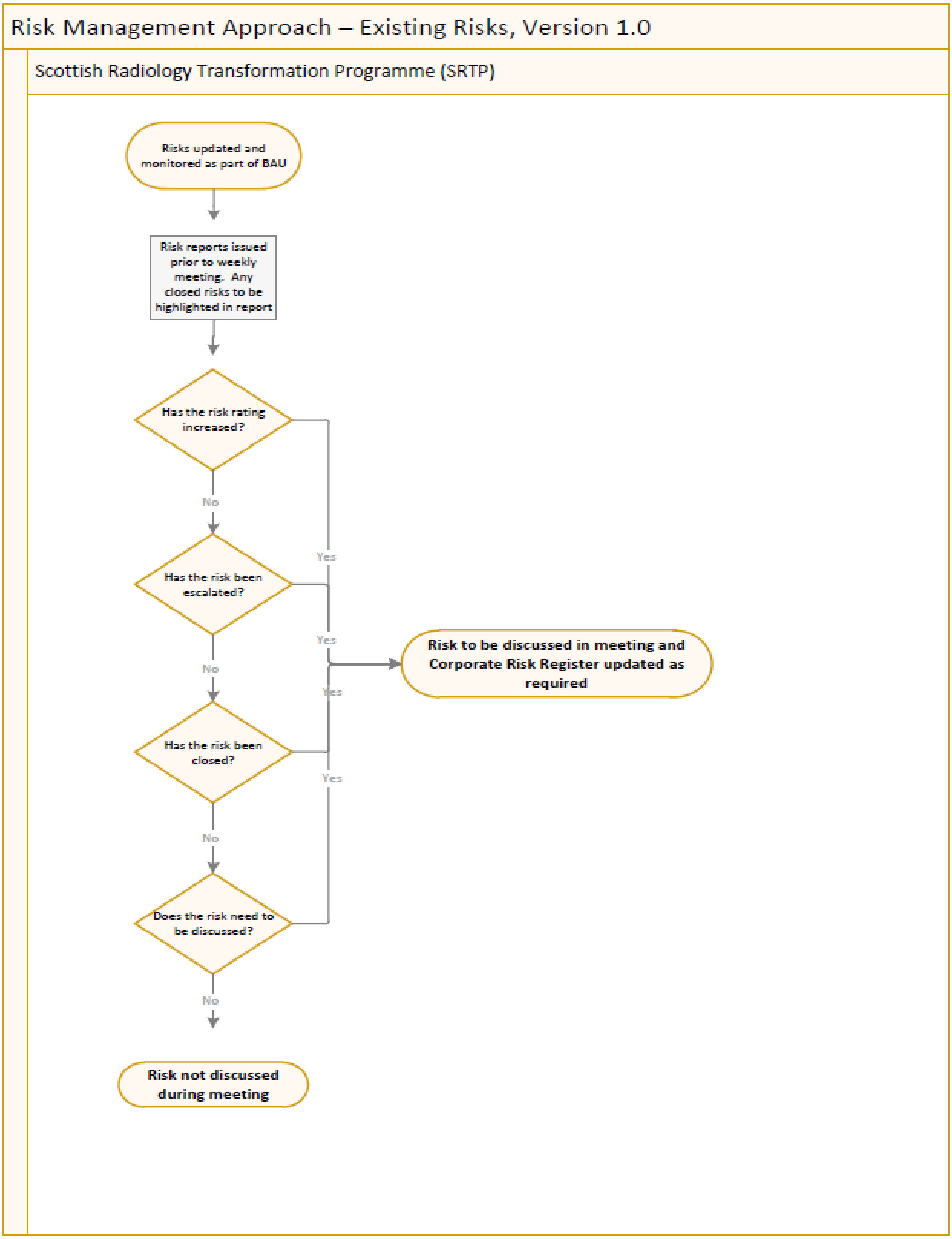




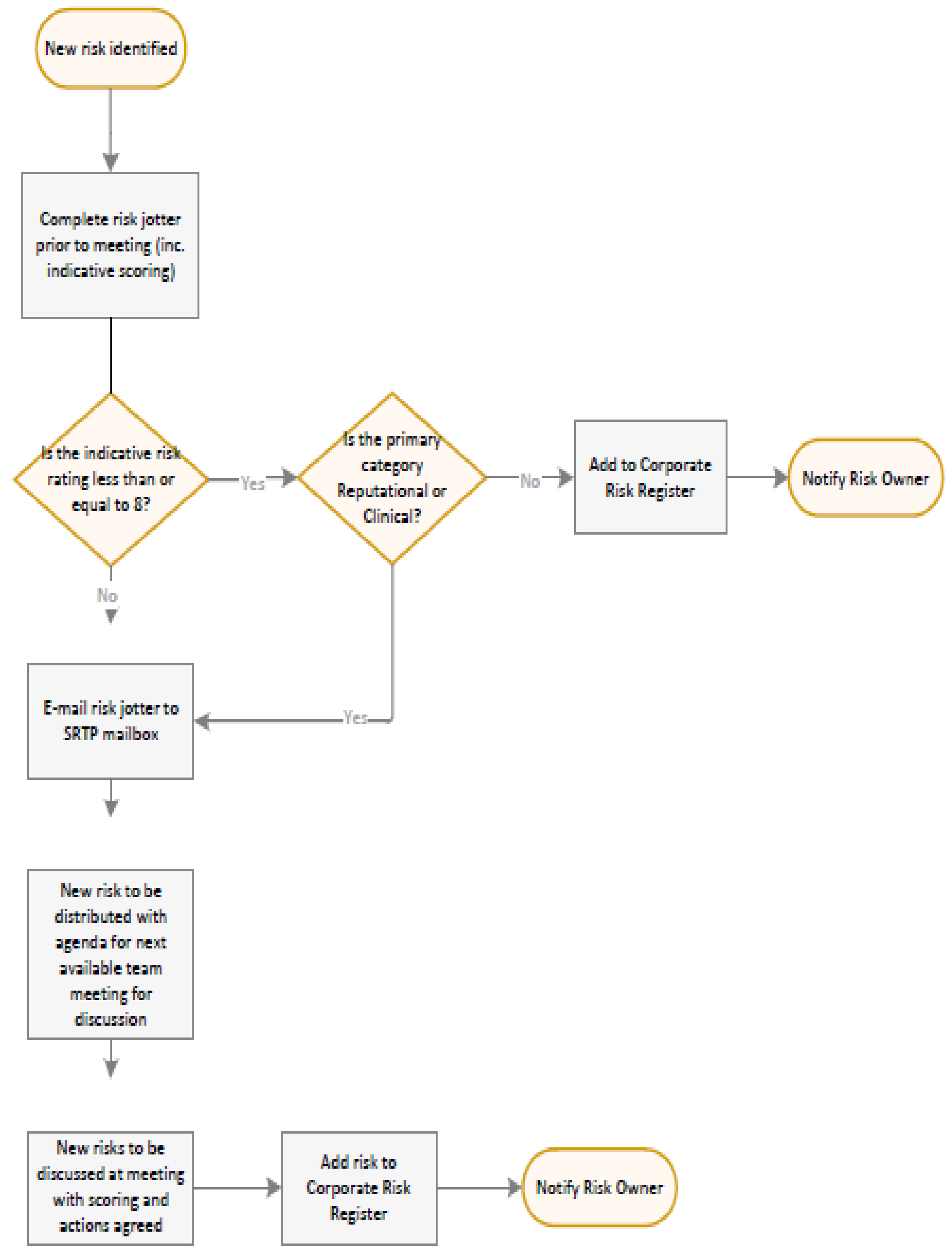

Option 2 – BAU and a new Radiology Programme
Apr 2020
Apr 2021
Apr 2022
Apr 2023
Apr 2024
Programme level activity
Set up
Closure
Scope AI
Workforce pilots
CDS pilots and implementation
BAU
Unfunded potential projects


Option 3 – BAU, a new Radiology Programme and Designing the Future
Apr 2020
Apr 2021
Apr 2022
Apr 2023
Apr 2024
Programme level activity
Set up
Closure
Scope AI
Workforce pilots
CDS pilots and implementation
Unfunded potential projects
Designing a new model for Radiology

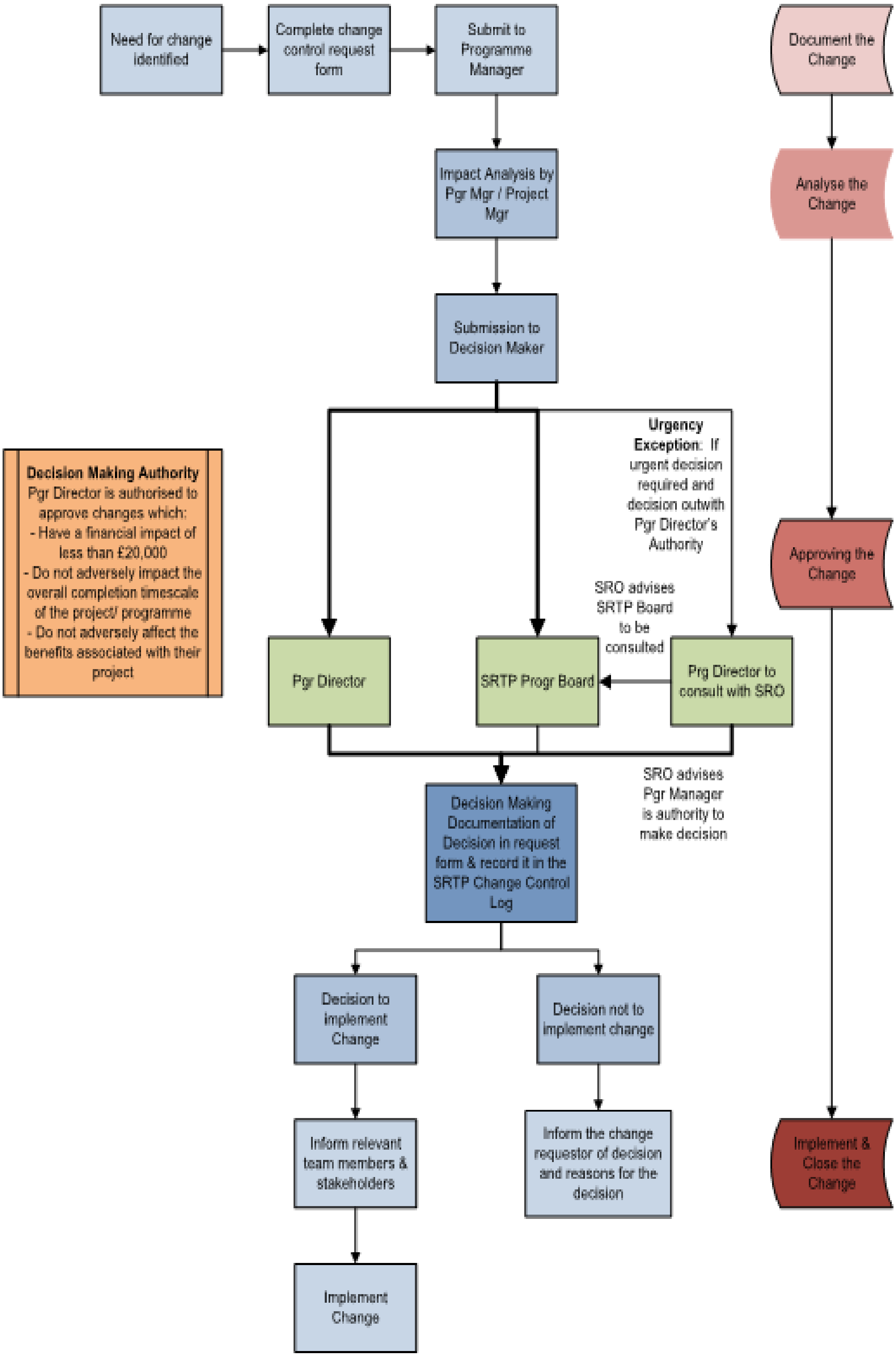
Appendix 16. Risk Management Approach



Scottish Radiology Transformation Programme (SRTP)



Appendix 17. Change Management



Appendix 18. Glossary & Terminology

Glossary	
BaU	Business as Usual Completed project delivery that has been handed over to a operational team needing an open ended revenue budget and governance arrangements
BI	Business Intelligence
CLO	NSS Central Legal Office
Cost Book	Scottish Health Services Costs
GEM	Generic Economic Model
GMC	General Medical Council
ISD	NSS Information and Statistics Division
MRI	Magnetic Resonance Imaging
NPC	Net Present Cost
NPV	Net Present Value
NRAC	National Resource Allocation Model
NRIIP	National Radiology Information and Intelligence Project
NSS	National Services Scotland
PgMS	Programme Management Services Within NSS Strategy, Performance and Service Transformation
PHI	NSS Public Health and Intelligence
RCR	Royal College of Radiologists
SHTG	Scottish Health Technologies Group
SNRRS	Scottish National Radiology Reporting System
SRTP	Scottish Radiology Transformation Programme

Terminology used	
2017 SRTP business case	NHS Scotland Shared Services National Radiology Programme business case (approved by CEs 8/8/17)
SRTP Phase 1 programme	The programme as delivered Aug 2017 - Sep2019
SRTP Phase 2 programme	The potential programme as detailed in this business case for Apr 2020 – March 2023
RCR workforce census 2018	Clinical radiology UK workforce census report 2018

Appendix 19. Business Case Development Discussion & Control

19.1 Key Information

Title	Scottish Radiology Transformation Programme (SRTP) Phase 2
Date Published / Issued	
Date Effective From	
Version / Issue Number	V0.00
Document Type	Business Case
Document Status	0.29 Draft
Author	Jim Cannon (Programme Director)/ Hamish McRitchie (Medical Director), Jill Patte (Programme Portfolio Manager)
Owner	Jill Patte (Programme Portfolio Manager)
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19.2 Revision History

Version	Date	Summary of Changes	Name	Changes Marked
v0.1-v0.22	Apr-18/ Oct-19	Initial Drafts	Jill Patte, SRTP Team	X

19.3 Approvals

This document requires the following signed approvals:

Version	Date	Name	Role	Signature
		Jill Patte	Project Portfolio Manager	
		Hamish McRitchie	Medical Director	

		Mary Morgan	SRO	
		Carolyn Low		
		Corporate Finance Network Group		
		Directors of Finance Group		
		Chief Executives Group		

19.4 Distribution

This document has been distributed to:

Version	Date of Issue	Name	Role / Area
		Jill Patte	Project Portfolio Manager / PgMS
		Carolyn Low	Director of Finance and Business Services
		Mary Morgan	SRO
	22/10/2019	Corporate Finance Network Group	
		Directors of Finance Group	
		Chief Executives Group	