United States Patent Application Publication	20250259747
Kind Code	A1
Publication Date	August 14, 2025
Inventor(s)	Chang; Jeffrey et al.

METHOD AND SYSTEM FOR THE COMPUTER-ASSISTED IMPLEMENTATION OF RADIOLOGY RECOMMENDATIONS

Abstract

A method for the computer-assisted implementation of radiology recommendations includes any or all of: receiving a set of inputs; determining and/or identifying a set of findings; determining a set of follow-up recommendations; and triggering a set of outputs and/or actions based on the set of follow-up recommendations. A system for the computer-assisted implementation of radiology recommendations preferably includes and/or interfaces a set of computing subsystems and/or processing subsystems, but can additionally include and/or interface with a set of devices (e.g., user devices), models, and/or any other components.

Inventors: **Chang; Jeffrey (Berkeley, CA), Gurson; Doktor (Berkeley, CA), Whitney; Scott (Berkeley, CA), Allen; Joseph Zachary (Berkeley, CA), Kazemlou; Shokoufeh (Berkeley, CA), Taylor; Maxwell (Berkeley, CA), Warner; Craig (Berkeley, CA), Purdy; Eric (Berkeley, CA), Johnson; Christopher (Berkeley, CA)**

Applicant: **RAD AI, Inc.** (San Francisco, CA)

Family ID: **96659929**

Assignee: **RAD AI, Inc. (San Francisco, CA)**

Appl. No.: **19/174282**

Filed: **April 09, 2025**

Related U.S. Application Data

parent US continuation 17690751 20220309 parent-grant-document US 11615890 child US 18108615
parent US continuation 17690751 20220309 parent-grant-document US 11615890 child US 18108615
parent US continuation-in-part 18108615 20230211 ABANDONED child US 19174282
parent US continuation-in-part 18215354 20230628 PENDING child US 19174282

parent US continuation-in-part 18108615 20230211 ABANDONED child US 18215354
us-provisional-application US 63158706 20210309
us-provisional-application US 63158706 20210309

Publication Classification

Int. Cl.: **G16H50/20** (20180101); **G16H10/60** (20180101); **G16H15/00** (20180101); **G16H40/20** (20180101); **G16H50/30** (20180101); **G16H70/20** (20180101)

U.S. Cl.:

CPC **G16H50/20** (20180101); **G16H10/60** (20180101); **G16H15/00** (20180101); **G16H40/20** (20180101); **G16H50/30** (20180101); **G16H70/20** (20180101);

Background/Summary

CROSS-REFERENCE TO RELATED APPLICATIONS [0001] This application is a continuation-in-part of U.S. application Ser. No. 18/108,615, filed 11 Feb. 2023, which is a continuation of U.S. application Ser. No. 17/690,751, filed 9 Mar. 2022, which claims the benefit of U.S. Provisional Application No. 63/158,706, filed 9 Mar. 2021, which is incorporated in its entirety by this reference. [0002] This application is also a continuation-in-part of U.S. application Ser. No. 18/215,354, filed 28 Jun. 2023, which is a continuation-in-part of U.S. application Ser. No. 18/108,615, filed 11 Feb. 2023, which is a continuation of U.S. application Ser. No. 17/690,751, filed 9 Mar. 2022, which claims the benefit of U.S. Provisional Application No. 63/158,706, filed 9 Mar. 2021, which is incorporated in its entirety by this reference.

TECHNICAL FIELD
[0003] This invention relates generally to the radiology field, and more specifically to a new and useful system and method for computer-assisted implementation of radiology recommendations in the radiology field.
BACKGROUND
[0004] In current radiology workflows, one of the radiologist's main responsibilities is to identify, record, and make recommendations on his or her findings from the study (e.g., imaging, exam, etc.) in the radiology report. During this, the radiologist is typically most concerned with standard findings (equivalently referred to herein as critical findings), which refer to findings associated with the original intent of the study. However, oftentimes, there are other findings-incidental findings-which are not the original intent of the study, but could have (e.g., according to consensus guidelines, according to best practices, etc.) associated follow-up procedures (e.g., follow-up imaging, follow-up procedures, monitoring, etc.).
[0005] The reliability and consistency with which radiologists include follow-up recommendations for incidental findings in the report is highly variable among radiologists and even for individual radiologists. As such, it has been found that less than half (e.g., ˜40%) of studies with significant incidental findings include specific recommendations for follow-up, and in only a small percentage (e.g., ˜25%) of those cases is the follow-up actually performed.
[0006] To further compound the unreliability of addressing incidental findings, even when the incidental findings are noted in the report, the actual follow-up is poor, which can lead to any or all of: a missed opportunity for revenue (e.g., lack of follow-up imaging, lack of follow-up procedures associated with incidental findings, etc.) for the healthcare facility and/or radiology group, increased liability (e.g., for missing incidental findings, for missing follow-up, etc.) for the

healthcare facility and/or radiology group, harm (e.g., illness, death, etc.) to the patient, or any number of other negative outcomes.
[0007] Thus, there is a need in the radiology field to create an improved and useful system and method for identifying, tracking, and following up with radiology findings and their associated recommendations.

Description

BRIEF DESCRIPTION OF THE FIGURES
[0008] FIG. **1** is a schematic of a method for identifying and tracking radiology findings.
[0009] FIGS. **2**A-**2**D depict variations of radiology reports and associated prompts related to the method **100**.
[0010] FIG. **3** depicts a variation of a decision tree in performing any or all of the method **100**.
[0011] FIGS. **4**A-**4**B depict a variation of the method for identifying and tracking radiology findings.
[0012] FIG. **5** depicts a variation of the processing of a radiology report.
[0013] FIG. **6** depicts a variation of a system for identifying and tracking radiology findings, along with information flows involved in a variation of a method for identifying and tracking radiology findings.
[0014] FIGS. **7**A-**7**E depict specific examples of the determination, triggering, and management of a set of actions and/or outputs associated with follow-up recommendations for a set of patients.
[0015] FIG. **8** depicts an example of notifying a user based on a comparison between a finding classification determined using a radiology report and a finding classification determined using radiology images.
[0016] FIGS. **9**A-**9**B depict examples of generating radiology report text.
[0017] FIG. **10** depicts an example of flagging patients.
[0018] FIG. **11** depicts an example of adjusting a radiology report and providing the adjusted radiology report to a user.
[0019] FIG. **12**A depicts an illustrative example of flagging an ineligible patient.
[0020] FIG. **12**B depicts an illustrative example of tracking a patient and flagging an exam schedule.
[0021] FIGS. **13**A-**13**B depict illustrative examples of lung cancer screening (LCS) workflows.
[0022] FIGS. **14**A-**14**B depict embodiments of system components structured to process radiology reports and automatically generate follow-up recommendations with a minimal-input approval tool for executing recommended actions.
[0023] FIGS. **15**A-**15**B depict examples of interfaces associated with the system shown in FIGS. **14**A-**14**B.
[0024] FIGS. **16**A-**16**B depict embodiments of method steps for processing radiology reports and automatically generating follow-up recommendations with a minimal-input approval tool for executing recommended actions.
DESCRIPTION OF THE PREFERRED EMBODIMENTS
[0025] The following description of the preferred embodiments of the invention is not intended to limit the invention to these preferred embodiments, but rather to enable any person skilled in the art to make and use this invention.
1. Overview
[0026] As shown in FIG. **1**, a method **100** for the computer-assisted implementation of radiology recommendations includes any or all of: receiving a set of inputs S**100**; determining and/or identifying a set of findings S**200**; determining a set of follow-up recommendations S**300**; and triggering a set of outputs and/or actions based on the set of follow-up recommendations S**400**.

Additionally or alternatively, the method **100** can include any or all of the methods, processes, embodiments, and/or examples described in any or all of: U.S. application Ser. No. 16/688,623, filed 19 Nov. 2019, and U.S. application Ser. No. 17/020,593, filed 14 Sep. 2020, each of which is incorporated in its entirety by this reference, or any other suitable processes performed in any suitable order.

[0027] The method **100** is preferably performed with a system **200** as described below, but can additionally or alternatively be performed with any suitable system(s), such as, but not limited to, any or all of systems, components, embodiments, and/or examples described in any or all of the applications referenced and incorporated above.

[0028] As shown in FIG. **6**, a system **200** for the computer-assisted implementation of radiology recommendations preferably includes and/or interfaces a set of computing subsystems and/or processing subsystems, but can additionally include and/or interface with a set of devices (e.g., user devices), models, and/or any other components. Additionally or alternatively, the system **200** can include and/or interface with any or all of the systems, components, embodiments, and/or examples as described in U.S. application Ser. No. 16/688,623, filed 19 Nov. 2019, and/or U.S. application Ser. No. 17/020,593, filed 14 Sep. 2020, each of which is incorporated in its entirety by this reference.

2. Benefits

[0029] The method and system for automatically identifying and tracking radiology findings can confer several benefits over current systems and methods.

[0030] While radiology reports are described, the invention(s) described herein can be adapted to and provide benefits upon processing non-radiology reports (e.g., reports associated with a clinical environment, reports not associated with a clinical environment)

[0031] In one aspect, the inventions include and implement advanced models for performing one or more of: automatically extracting findings from radiology reports, generating summaries of findings, organizing findings (e.g., by category, by subcategory), rendering finding summaries at an interface of a radiology system, rendering follow-up recommendations pertaining to the finding summaries at the interface for review and approval by users of the interface, providing one or more objects at the interface by which users can efficiently approve and initiate execution of the follow-up recommendation(s), confirming completion of the follow-up recommendation(s), training the advanced model(s) to continuously improve efficiency by which follow-up recommendations are generated, training the advanced model(s) to continuously improve accuracy of finding summarizations by which follow-up recommendations are generated, training the advanced model(s) to continuously improve appropriateness of follow-up recommendations, and generating other relevant outputs.

[0032] In another aspect, additional or alternative to those described, the method confers the benefit of automatically determining any or all of the incidental findings, automatically determining and/or generating any or all of the associated follow-up recommendations for the incidental findings, and/or partially or fully automating any or all of the processes of the method. In specific examples, a set of trained models (e.g., machine learning models, deep learning models, etc.) can be used for any or all of: automatically determining a set of findings (e.g., incidental findings); automatically creating and/or filling in any or all of the radiology report; automatically triggering actions; and/or any other suitable processes.

[0033] In another aspect, additional or alternative to those described, the methods and systems described can significantly increase efficiency of systems used to execute follow-up actions and process radiology report backlogs, in relation to number of full time equivalent (FTE) personnel required to perform work (e.g., review findings from radiology reports, execute recommended follow-up actions to “close the loop” responsive to the finding(s) in the radiology report(s)). In examples, the methods and systems described can provide a novel interface by which a user (e.g., navigator) can be presented with finding summaries and approve execution of follow-up recommendations, in a manner that significantly reduces FTE numbers required to process a number of reports. As such, the inventions described can clear backlogs by executing follow-up recommendations in an unprecedented manner. In examples, the interface can reduce a number of full-time equivalent (FTE) users required to initiate execution of follow-up recommendations for a set of radiology reports by at least: 50%, 55%, 60%, 65%, 70%, 75%, 80%, 85%, 90%, 95%, 100%, or greater, depending upon institutional requirements and/or other factors.

[0034] In relation to provision of a novel interface with the performance attributes described, embodiments of methods described can include: providing an interface for single-input approval of a clinical follow-up recommendation generated automatically using a trained multi-transformer model, upon: receiving a radiology report associated with a set of radiology images from a patient of an institution, from a Picture Archiving and Communication System (PACS) or other image handling system; processing the radiology report with the trained multi-transformer model to determine a set of classifications, the method further comprising generating the trained multi-transformer model upon training, with a computing subsystem remote from the PACS, a multi-transformer model with training data from reports from a set of institutions and involving a set of actionable findings; at the interface, returning: a) a finding summary for the radiology report, from the trained multi-transformer model, b) a set of follow-up recommendations comprising a promoted follow-up recommendation from the trained multi-transformer model, and c) an input-receiving object for approving execution of the promoted follow-up recommendation; upon receiving a single-input to the input-receiving object from a user of the interface, executing the promoted follow-up recommendation by providing computer-readable instructions for a Radiology Information System (RIS); and confirming completion of the promoted follow-up recommendation for a patient upon interrogating the Radiology Information System (RIS).

[0035] Relatedly, embodiments of a system can include: an interface configured for single-input approval of a clinical follow-up recommendation; and a processing system in communication with the interface, a Picture Archiving and Communication System (PACS), and a Radiology Information System (RIS) and comprising a trained multi-transformer model, wherein the computing system comprises instructions stored in a non-transitory medium that, when executed, perform; generating the trained multi-transformer model upon training, with a computing subsystem remote from the PACS, a multi-transformer model with training data from reports from a set of institutions and involving a set of actionable findings; receiving a radiology report associated with a set of radiology images from a patient of an institution, from the PACS; processing the radiology report with the trained multi-transformer model to determine a set of classifications; causing to render, at the interface: a) a finding summary for the radiology report, from the trained multi-transformer model, b) a set of follow-up recommendations comprising a promoted follow-up recommendation from the trained multi-transformer model, and c) an input-receiving object for approving execution of the promoted follow-up recommendation; upon receiving a single-input to the input-receiving object from a user of the interface, executing the promoted follow-up recommendation by providing computer-readable instructions for a Radiology Information System (RIS); and confirming completion of the promoted follow-up recommendation for a patient upon interrogating the RIS.

[0036] As such, in variations, the interface provides mechanism for executing follow-up recommended actions responsive to findings extracted from radiology reports by artificial intelligence (AI) models, upon acceptance of a single input from a user of the interface. Furthermore, in specific examples, any or all of the method can performed in absence of input from a radiologist or other user, which can be equivalently referred to herein as a “zero-click” process.

[0037] In variations, models described (e.g., multi-transformer models) can incorporate large language model (LLM) architecture and/or non-LLM architecture. Models can be multimodal.

[0038] In examples, LLM architecture can include a version of the Pathways Language Model (e.g., PaLM, PaLM2, etc.). Variations of the LLM can include a version of a Language Model for

Dialogue Applications (LaMDA), a Gemini model (e.g., a decoder-only transformer), a GPT model, a Llama model, a GLM model, a Claude model, a Reka Flash model, a Qwen model, a Grok model, a Molmo model, a Jamba model, a DeepSeek Coder model, an Athene model, a Phi-3 model, a Command-R-Plus model, an InternLM model, a Yi-Large model, a Mixtral of Experts model, a Gemma model, a Nemotron model, and/or another suitable model.

[0039] In another aspect, the systems and methods described can pre-process a historical backlog of radiology reports, such that new users of the invention(s) and/or interfaces described are immediately presented with tools for efficiently processing the historical backlog. In examples, the systems and methods described can pre-process up to 6 months of a historical backlog of radiology reports, up to 1 year of a historical backlog of radiology reports, up to two years of a historical backlog of radiology reports, up to 3 years of a historical backlog of radiology reports, up to 4 years of a historical backlog of radiology reports, up to 5 years of a historical backlog of radiology reports, up to 6 years of a historical backlog of radiology reports, up to 7 years of a historical backlog of radiology reports, up to 8 years of a historical backlog of radiology reports, up to 9 years of a historical backlog of radiology reports, up to 10 years of a historical backlog of radiology reports, or greater. Pre-processing can include generating, for each report in the historical backlog, a finding summary and a set of follow-up recommendations (including a promoted follow-up recommendation that can be executed with a single-input approval action). Processing the historical backlog of radiology reports can further include one or more of: providing a historical benchmark of performance for processing radiology reports (e.g., at the institution); using historical backlog to train the model(s) described for automatically extracting findings and returning finding summaries and promoted follow-up recommendations for approval and execution.

[0040] In variations, a finding summary of extracted findings can include finding categorizations and finding subcategorizations, where categorizations and subcategorizations are described in relation to classifications and other features described below.

[0041] In variations, during an initial interaction with the interface, a user can be presented with a backlog of finding summaries generated from historical radiology reports, along with corresponding promoted recommended follow-up actions. As such, methods described can include presenting an organized set of finding summaries paired with a set of promoted follow-up recommendations generated upon processing a backlog of radiology reports with the trained multi-transformer model, for an institution, at an initial interaction with the interface. In examples, the methods and systems described can reduce the historical backlog of open radiology reports by at least 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90%, or greater, within 7 days, within 6 days within 5 days, within 4 days, within 3 days, within 2 days, within 1 day, within 22 hours, within 20 hours, within 18 hours, within 16 hours, within 14 hours, within 12 hours, within 10 hours, within 8 hours, within 6 hours, within 4 hours, or less, upon receiving a set of single-inputs for executing a subset of the set of promoted follow-up recommendations, at the interface.

[0042] In another aspect, the methods and systems described can provide, mechanisms for confirming completion of a recommended follow-up (e.g., promoted recommended follow-up, where the promoted recommended follow-up is the most appropriate or highest-ranked follow-up action in a list of recommended follow-up candidates), In one example, confirming completion of the follow-up recommendation can include receiving a notification, at an embodiment of the interface described, that the promoted follow-up recommendation was completed, upon interrogating the patient using a natural language processing (NLP)-enhanced messaging tool by the system, and transmitting the notification to be rendered at the interface. Completion of the promoted follow-up recommendation can be performed at the institution where the user interacts with the interface, or alternatively, at a second institution different than the institution. As such, tracking of follow-up completion can be performed automatically, using the NLP-enhanced messaging tool, regardless of which institution cares for a patient. NLP-enhanced messaging tools associated with the systems and interfaces described can implement one or more of a variety of

algorithms structured to analyze, understand, and generate human language. In examples, the NLP-enhanced messaging tool can implement one or more of: Rule-based algorithms (e.g., Regular Expressions and Context-Free Grammars) structured to process text based on predefined linguistic rules; Classical machine learning techniques (e.g., Naïve Bayes algorithms, Support Vector Machines (SVM), Hidden Markov Models (HMM)) structured for tasks such as text classification, named entity recognition, and part-of-speech tagging; Deep learning models (e.g., Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Transformers (such as BERT and GPT)) structured for contextual understanding and generation of human-like text; word embedding techniques (e.g., Word2Vec, GloVe, FastText) structured to capture semantic meanings by representing words in high-dimensional vector spaces; Sequence-to-sequence (Seq2Seq) models leveraging attention mechanisms structured for tasks like machine translation and text summarization; Generative Adversarial Networks (GANs) structured for text and reinforcement learning-based approaches; and other model architecture.
[0043] In another aspect, the methods and systems described can be structured to drive flow of information through systems associated with radiology healthcare. As such, methods and systems described can drive flow of information (e.g., through a RIS), with execution of a follow-up recommendation and confirmation of completion of the promoted follow-up recommendation.
[0044] In another aspect, the method and/or system confer the benefit of ensuring that incidental findings are present in a radiology report and/or that appropriate follow-up (e.g., according to the radiologist, according to the patient's clinicians, according to national consensus guidelines, etc.) for the incidental findings is included and adhered to, which can in turn confer numerous benefits in promoting preventative care. In specific examples, adhering to follow-up can include any or all of: ensuring that appropriate follow-up is communicated to the clinician(s) (e.g., patient's primary care physician) who will ultimately be responsible for ordering the follow-up study or consultation and/or for caring for the patient long-term as an outpatient; ensuring that the appropriate follow-up is communicated clearly to the patient, so that the patient understands the follow-up and its potential impact on the patient's long-term health; ensuring that appropriate follow-up is performed according to a particular (e.g., recommended) timeline; reducing liability of physicians (e.g., primary care physicians, ER doctors, radiologists, etc.) and/or radiology groups and/or healthcare facilities which results from not properly communicating and/or enforcing follow-up recommendations; reducing costs in the health care system associated with the delayed response to and/or lack of response to detected incidental findings; facilitating the matching of a patient with a PCP (e.g., in an event that the patient does not have a PCP); and/or adhering to follow-up recommendations in any other way(s).
[0045] In another aspect, additional or alternative to the first, the method confers the benefit of triggering an action in response to follow-up recommendations associated with the incidental findings, which can function to ensure that the follow-up recommendations are performed (e.g., immediately, over a significant time period, during a change in clinician associated with the patient, etc.). In specific examples, the triggered actions can include any or all of: pulling another physician (e.g., emergency room [ER] physician, patient's primary care physician, on-call physician, etc.) into the loop (e.g., notifying the physician, assigning the physician to the patient, etc.); establishing communication between individuals and/or entities (e.g., between an ER physician and a primary care physician, between the patient and a physician, etc.); setting automated reminders; automatically scheduling actions (e.g., lab work, imaging, examinations, specialist appointments, etc.) associated with the follow-up recommendations; facilitating the matching of a patient with a primary care physician (PCP) in an event that the patient does not have a PCP; and/or any other actions.
[0046] In another aspect, additional or alternative to those described above, the system and/or method confer the benefit of establishing uniformity (e.g., a set of uniform processes, guidelines, etc.) in detecting, determining, and/or responding to follow-up recommendations associated with

incidental findings (e.g., significant incidental findings).

[0047] In another aspect, additional or alternative to those described above, the system and/or method confer the benefit of detecting and/or locating information within various different types, formats, and/or organizational styles of radiology reports or any other documents. In a set of specific examples, a set of trained models is used to locate incidental findings and/or follow-up recommendations within a radiology report (e.g., from an unspecified section in a radiology report). Additionally, a set of rule-based logic can optionally be used in combination with the trained models.

[0048] Additionally or alternatively, the system and method can confer any other benefit.

3. System

[0049] As shown in FIGS. **14**A and **14**B, an embodiment of a system **200** can include and/or interface with any or all of: one or more models/modules **210**, a computing system **220**, a database **230**, a user interface (e.g., a radiology dashboard **235**), user devices (e.g., a radiology workstation), and/or any other suitable system components. As shown in FIG. **14**B, the system **100** can include and/or interface with any or all of: one or more models **210**, a computing system **220** (including a local computing system **221** and/or a remote computing system **222**), a set of databases **230**, a user interface (e.g., referred to equivalently herein as an “input interface”), a reporting platform **240**, user devices, and/or any other suitable system components.

[0050] Additionally or alternatively, the system can include any or all of the components as described in any or all of: U.S. application Ser. No. 16/688,623, filed 19 Nov. 2019; U.S. application Ser. No. 17/020,593, filed 14 Sep. 2020; U.S. application Ser. No. 17/690,751, filed 9 Mar. 2022; U.S. application Ser. No. 18/215,354, filed 28 Jun. 2023; U.S. application Ser. No. 17/649,213, filed 28 Jan. 2022; U.S. application Ser. No. 18/374,535, filed 28 Sep. 2023; and U.S. application Ser. No. 18/374,526, filed 28 Sep. 2023, each of which is incorporated in its entirety by this reference.

[0051] The system is preferably used by a radiologist, but can additionally or alternatively be used by any medical professional (e.g., physician, specialist, nurse, etc.), a patient (e.g., wherein the system is configured to display relevant information in a patient's history to the patient alongside their images), and/or any other suitable user (e.g., navigator, coordinator, radiology technologist, scheduling team member, user, etc.). As referred to herein, “user” and “radiologist” can be used interchangeably, but other users can be understood to use the system.

[0052] The system **200** functions to automatically retrieve and render radiology information to a clinical entity (e.g., radiologist) that can be utilized (e.g., by a radiologist, by additional automated processes, etc.) to increase radiology workflow efficiency, in relation to method steps described. For instance, the system **200** can surface finding summaries and follow-up recommendations in the most efficient manner, with the ability to accept single or minimal inputs for executing promoted follow-up recommendations. Additionally or alternatively, the system **200** can function to: increase an accuracy, comprehensiveness, or other metric(s) of a produced radiology report, by dynamically informing a radiologist with relevant information as they prepare reports and/or review information (e.g., findings, images); produce an entire radiology report and/or preliminary radiology report (e.g., radiology report without impression section, draft radiology report, etc.); and/or otherwise suitably function.

[0053] In embodiments, variations, and examples, the system **100** includes multimodal models with large language model (LLM) architecture and/or non-LLM architecture that can improve functionality of radiology systems (e.g., radiology report systems) that support radiologists in processing their respective worklists, in relation to workflow resolution enhancements.

[0054] In examples, increased efficiency/speed performance can be attributed to the system **200** and methods **100** described, whereby increased speed performance can be evaluated in relation to number of full time equivalent (FTE) personnel required to perform work (e.g., review findings from radiology reports, execute recommended follow-up actions to “close the loop” responsive to

the finding(s) in the radiology report(s)). In examples, systems described can provide a novel interface by which a user (e.g., navigator) can be presented with finding summaries and approve execution of follow-up recommendations, in a manner that significantly reduces FTE numbers required to process a number of reports. As such, the systems described can clear backlogs by executing follow-up recommendations in an unprecedented manner. In examples, the interface can reduce a number of full-time equivalent (FTE) users required to initiate execution of follow-up recommendations for a set of radiology reports by at least: 50%, 55%, 60%, 65%, 70%, 75%, 80%, 85%, 90%, 95%, 100%, or greater, depending upon institutional requirements and/or other factors.
[0055] In examples, detection sensitivity performance is also attributed to the systems **200** and methods **100** described. In examples, the system **100** provided: greater than 70% sensitivity (e.g., in detection of a clinical indication, such as an intracranial hemorrhage), greater than 71% sensitivity (e.g., in detection of a clinical indication, such as an intracranial hemorrhage), greater than 72% sensitivity (e.g., in detection of a clinical indication, such as an intracranial hemorrhage), greater than 73% sensitivity (e.g., in detection of a clinical indication, such as an intracranial hemorrhage), greater than 74% sensitivity (e.g., in detection of a clinical indication, such as an intracranial hemorrhage), greater than 75% sensitivity (e.g., in detection of a clinical indication, such as an intracranial hemorrhage), greater than 76% sensitivity (e.g., in detection of a clinical indication, such as an intracranial hemorrhage), greater than 77% sensitivity (e.g., in detection of a clinical indication, such as an intracranial hemorrhage), greater than 78% sensitivity (e.g., in detection of a clinical indication, such as an intracranial hemorrhage), greater than 79% sensitivity (e.g., in detection of a clinical indication, such as an intracranial hemorrhage), greater than 80% sensitivity (e.g., in detection of a clinical indication, such as an intracranial hemorrhage), greater than 85% sensitivity (e.g., in detection of a clinical indication, such as an intracranial hemorrhage), greater than 90% sensitivity (e.g., in detection of a clinical indication, such as an intracranial hemorrhage), or greater sensitivity.
[0056] In examples, detection specificity performance is also attributed to the system **200**. In examples, the system **100** provided: greater than 80% specificity (e.g., in detection of a clinical indication/anomaly), greater than 82% specificity (e.g., in detection of a clinical indication/anomaly), greater than 84% specificity (e.g., in detection of a clinical indication/anomaly), greater than 86% specificity (e.g., in detection of a clinical indication/anomaly), greater than 88% specificity (e.g., in detection of a clinical indication/anomaly), greater than 90% specificity (e.g., in detection of a clinical indication/anomaly), greater than 92% specificity (e.g., in detection of a clinical indication/anomaly), greater than 94% specificity (e.g., in detection of a clinical indication/anomaly), greater than 96% specificity (e.g., in detection of a clinical indication/anomaly), greater than 98% specificity (e.g., in detection of a clinical indication/anomaly), or greater specificity. Specificity can be determined based upon determination of false positive and/or false negative metrics, with respect to anomaly detection/clinical indication detection according to methods described, and involving use of systems described.
[0057] As shown in FIGS. **14**A and **14**B, the system **200** includes a set of models **110**, which function to perform any or all of the processing, generation, training, re-training, transmission, action execution, and/or other steps in the methods **100** (e.g., as described below). Variations of models can include LLM and/or non-LLM architecture, and/or any other model used to generate finding summaries and follow-up recommendations. The models can include architecture for machine learning approaches, classical or traditional approaches, and/or be otherwise configured. The models can include neural networks (e.g., CNN; DNN; CAN; LSTM; RNN such as LSTM, GRU, etc.; FNN; encoders; decoders; deep learning models; transformers; etc.) configured with image encoder architecture and large language model (LLM) architecture, regression, decision tree, LSA, clustering, association rules, dimensionality reduction, ensemble methods, optimization methods, classification, rules, heuristics, equations (e.g., weighted equations, etc.), selection (e.g.,

from a library), regularization methods (e.g., ridge regression), Bayesian methods (e.g., Naiive Bayes, Markov), instance-based methods (e.g., nearest neighbor), kernel methods, support vectors (e.g., SVM, SVC, etc.), statistical methods (e.g., probability), comparison methods (e.g., ranking, similarity, matching, distance metrics, thresholds, etc.), deterministics, genetic programs, and/or any other suitable model. The models can include (e.g., be constructed using): a set of input layers (e.g., encoders), output layers (e.g., decoders such as beam search decoders), and/or hidden layers (e.g., connected in series, such as in a feed forward network; connected with a feedback loop between the output and the input, such as in a recurrent neural network; etc.; wherein the layer weights and/or connections can be learned through training); a set of connected convolution layers (e.g., in a CNN); attention mechanisms (e.g., sequence-to-sequence architecture; a set of attention layers and/or self-attention layers; etc.); and/or have any other suitable architecture.

[0058] Models can be trained (e.g., pre-trained, retrained, tuned, fine-tuned, etc.), learned, fit, predetermined, untrained, and/or can be otherwise determined. The models can be trained or learned using: supervised learning, unsupervised learning, self-supervised learning, semi-supervised learning (e.g., positive-unlabeled learning), reinforcement learning, transfer learning, Bayesian optimization, fitting, interpolation and/or approximation, backpropagation, and/or otherwise generated. Models can be trained using feedback from inputs/queries provided by a working radiologist at user interface **235** (e.g., in response to received inputs for executing follow-up recommendations, where the selected follow-up recommendation and the associated finding(s) can be used as training data to further refine the model(s) used), retrieved and rendered information at the radiology workstation, followed by further inputs/queries provided by the working radiologist. The further inputs/queries provided by the working radiologist can be used to refine the models described, where such inputs can indicate relevancy of the rendered information, such that improved information retrieval and rendering can be performed.

[0059] Additionally or alternatively in other examples, models can be trained based on historical radiology reports (e.g., annotated radiology reports from a historical backlog, or as the user processes an initial backlog of reports during an initial session with the interface), manually generated radiology reports, synthesized radiology reports, labeled data, unlabeled data, positive training sets, negative training sets, and/or any other suitable set of data. Models can optionally be trained and/or undergo post-processing using: an additional model (e.g., a first model is used to teach a second model), autonomous agents (e.g., while models interact with each other), and/or any other model interactions.

[0060] The set of models **210** can include multimodal models that can receive inputs and/or queries (e.g., text-based queries, dictation-based queries, text-based inputs, dictation-based inputs, input device inputs, image data inputs, and/or other inputs), and return radiology outputs that have been actively transformed in a manner that provides key information to the querying entity/input-providing entity, in a format that increases working efficiency. In variations and examples described, the trained multimodal models can be used to process inputs, retrieve information, and render information rapidly, with respect to durations of time from input to rendering. In examples, durations of time can be less than 3 seconds, less than 2 seconds, less than 1 second, less than 0.5 seconds, less than 0.25 seconds, less than 0.1 seconds, less than 0.005 seconds, or less. Furthermore, rendered information can be dynamically updated with unprecedented performance, as the querying entity/input-providing entity continues to work and provide further inputs, where dynamically updating rendered information can include removing or moving positions of prior provided information, and placing updated information that has been retrieved, in position at the user interface (e.g., in a manner that highlights relevant information to improve working efficiency).

[0061] The set of models can thus include image models (e.g., vision models, trained transformers, deep learning transformers, machine learning transformers, neural networks, recurrent neural networks, etc.), wherein the set of image models are collectively configured to translate image-based information into a representation (e.g., embeddings) that are processed with text embeddings by a language-based model (e.g., large language model (LLM), natural language model, etc.), wherein this translation, is used to process multimodal inputs and provide multimodal outputs. Additional aspects of multimodal modals are described in more detail below.

[0062] The set of models can further include NLP models in order to enable automation of text and/or audio-based communications through the system. For instance, the system can include and provide a (NLP)-enhanced messaging tool, with functionality for transmission of notifications to users (e.g., notifications to be rendered at the interface(s) described). NLP-enhanced messaging tools associated with the systems and interfaces described can implement one or more of a variety of algorithms structured to analyze, understand, and generate human language. In examples, the NLP-enhanced messaging tool can implement one or more of: Rule-based algorithms (e.g., Regular Expressions and Context-Free Grammars) structured to process text based on predefined linguistic rules; Classical machine learning techniques (e.g., Naïve Bayes algorithms, Support Vector Machines (SVM), Hidden Markov Models (HMM)) structured for tasks such as text classification, named entity recognition, and part-of-speech tagging; Deep learning models (e.g., Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Transformers (such as BERT and GPT)) structured for contextual understanding and generation of human-like text; word embedding techniques (e.g., Word2Vec, GloVe, FastText) structured to capture semantic meanings by representing words in high-dimensional vector spaces; Sequence-to-sequence (Seq2Seq) models leveraging attention mechanisms structured for tasks like machine translation and text summarization; Generative Adversarial Networks (GANs) structured for text and reinforcement learning-based approaches; and other model architecture.

[0063] The set of models preferably includes models implementing parallelization (e.g., processing all tokens at the same time) wherein processing data in order is not required, which can function to reduce training times and processing times. In preferred variations, for instance, the set of models includes a set of one or more transformers. In specific examples, for instance, the set of models includes a transformer model (equivalently referred to herein as a multi-transformer model) with one or more decoders that each consult a set of multiple encoders (e.g., in a sequential fashion, in a parallel fashion, etc.). As such, the trained multi-transformer model can include a set of decoders, each of the set of decoders structured to consult multiple encoders in parallel. In particular, the trained multi-transformer model can thus include parallelization architecture that does not require processing of data in any order.

[0064] The model(s) can be any or all of: trained, pretrained, fine-tuned or using other forms of transfer learning (e.g., based on a pretrained model), combined with one or more ontologies (e.g., radiological or other clinical ontology database), and/or any combination of these. In some variations, for instance, the set of models includes one or more trained and/or pretrained models which are fine-tuned based on radiology report language.

[0065] The set of models can optionally include and/or interface with a pre-processing module, which functions to clean up and/or otherwise modify data prior to training on and/or processing it. The pre-processing module is preferably implemented prior to or during the training of the model(s), but can additionally or alternatively be implemented on data serving as input to the trained model, and/or be implemented at any suitable time(s) during the method S**200** in any suitable way(s).

[0066] The set of models can optionally include and/or interface with a post-processing module, which functions to edit and/or otherwise modify one or more outputs produced by the set of models. This can include any or all of: formatting an output (e.g., an impressions section); further improving language styling to better match the style of the radiologist; checking and/or adjusting language for compliance with recommended and/or required language (e.g., medical classification lists such as the International Classification of Diseases and Related Health Problems [ICD], ICD-10, usage of word “indicates” for diagnoses to conform with billing guidelines and/or requirements, merit-based incentive payment system [MIPS] to help with and/or maximize reimbursement, consensus guidelines, etc.); notifying the radiologist of language which potentially may not conform with recommended and/or required language (e.g., as described above, so that the radiologist may manually edit, etc.); notifying a user (e.g., a radiologist, a navigator of a patient program, etc.) of a discrepancy between finding classifications; flagging a patient; adjusting a radiology report (e.g., prior to providing the adjusted radiology report to a patient and/or other user); and/or any other processing. Additionally or alternatively, any or all of the above can be performed in pre-processing, with the set of models, and/or at any suitable time(s) during the method **100** with any suitable models and/or modules.

[0067] The set of models is preferably located at (e.g., stored at, processed at, etc.) a computing subsystem (e.g., as described above), further preferably a remote computing subsystem (e.g., cloud computing system, remote server, etc.), but can additionally or alternatively be located at any or all of: a local computing subsystem, a combination of computing subsystems, and/or at any other suitable location(s).

[0068] The set of models can be configured to receive any number of inputs, such as, but not limited to, any or all of: a radiology report and/or any subset of a radiology report; a set of preferences; patient information (e.g., from the radiology report, from outside of the radiology report, from a historical radiology report, etc.); healthcare facility information; database information (e.g., from an EHR database, from an EMR database, from a PACS database, from a RIS database, etc.); guidelines (e.g., consensus guidelines, insurance guidelines, screening eligibility guidelines, etc.); radiology group information; radiology standards; billing procedures and/or guidelines; information from a database, storage, server, and/or software tools (e.g., EMR database, EHR database, RIS, CIS, PACS, etc.); a set of images (e.g., diagnostic images of the patient); video; and/or any other information from any suitable sources.

[0069] In examples, patient information can include: radiology reports (e.g., partially completed radiology reports, completed radiology reports, etc.), images (e.g., one or more sets of radiology images), findings, finding characteristics, finding classifications, recommendations, demographic information, clinical history and/or other patient history, information in an EHR and/or other database, laboratory and/or pathology results, patient vitals, ordering and/or scheduling information for exams (e.g., a current exam, prior exams, future exams, etc.), exam details, insights (e.g., output from one or more models; derived from the patient's prior radiology report(s) and/or other patient information), patient flags, and/or any other information associated with a patient.

[0070] In examples, findings can include: irregularities (e.g., anatomical irregularities), anatomical features such as nodules (e.g., masses, lesions, tumors, other growths, etc.), disease states, medical indications, illnesses, and/or other suitable features of a radiology image. In a specific example, findings can be associated with cancer (e.g., lung cancer, breast cancer, etc.). In an illustrative example, a finding can include a Lung-RADS finding (e.g., pulmonary nodules), a BI-RADS finding, a cardiac condition finding, another finding associated with oncology, and/or any other finding. In examples, finding characteristics can include measurements (e.g., size, diameter, volume, etc.), material composition (e.g., density; stiffness; tissue composition; solid, part-solid, and/or non-solid; etc.), shape (e.g., symmetric, asymmetric, smooth, lobulated, spiculated, oval shape, lentiform shape, triangular shape, etc.), location, calcification, cavitation, quantity (e.g., number of nodules), and/or any other characteristics of a finding. Finding characteristics can additionally or alternatively include a comparison between a first finding characteristic and a second finding characteristic (e.g., a change in a finding characteristic over time, across two sets of radiology images). In an illustrative example, finding characteristics can include nodule growth. Finding characteristics can additionally or alternatively include an aggregate of finding characteristics (e.g., across a single nodule, across multiple nodules within a set of radiology images, etc.). In an illustrative example, the finding characteristics can include a mean diameter for a nodule (e.g., average of long axis and short axis diameter). In another illustrative example, the finding characteristics can include an aggregate (e.g., mean, maximum, etc.) of one or more finding characteristics across a subset of the set of nodules (e.g., the nodules with the highest degree of suspicion). In examples, finding classifications can include scores (e.g., cancer screening score, any other screening score for a disease, etc.); incidental versus non-incidental; abnormal versus normal; positive versus negative; significant versus insignificant; and/or any other classification of a finding. In a first illustrative example, lung nodules can be classified with a Lung-RADS category (e.g., 0, 1, 2, 3, 4A, 4B, 4X, etc.), BI-RADS category, and/or any other cancer screening score. Finding classifications can optionally include modifiers (e.g., an ‘S’ modifier can optionally be added to a Lung-RADS category). Finding characteristics and/or classifications can be qualitative, quantitative, relative, discrete, continuous, a classification, numeric, binary (e.g., relative to a threshold), and/or otherwise configured.

[0071] The computing system **220** or other associated processing system can include one or more: CPU, GPUs, custom FPGA/ASICS, processors, microprocessors, servers, cloud computing, storage; memory; and/or any other suitable components. The computing system can be local (e.g., as a local computing system **221**), remote (e.g., as a remote computing system **222**), distributed, or otherwise arranged relative to any other system or module. The computing system **220**/processing system is preferably in communication with the interface **235** described, a Picture Archiving and Communication System (PACS), and a Radiology Information System (RIS) and comprising a trained multi-transformer model, wherein the computing system comprises instructions stored in a non-transitory medium that, when executed, perform method steps described, including; generating the trained multi-transformer model upon training, with a computing subsystem remote from the PACS, a multi-transformer model with training data from reports from a set of institutions and involving a set of actionable findings; receiving a radiology report associated with a set of radiology images from a patient of an institution, from the PACS; processing the radiology report with the trained multi-transformer model to determine a set of classifications; causing to render, at the interface: a) a finding summary for the radiology report, from the trained multi-transformer model, b) a set of follow-up recommendations comprising a promoted follow-up recommendation from the trained multi-transformer model, and c) an input-receiving object for approving execution of the promoted follow-up recommendation; upon receiving a single-input to the input-receiving object from a user of the interface, executing the promoted follow-up recommendation by providing computer-readable instructions for a Radiology Information System (RIS); and confirming completion of the promoted follow-up recommendation for a patient upon interrogating the RIS. The input-receiving object can include one or more of: follow-up action approval button, follow-up action disapproval button, button for executing alternative follow-up action, button for generating a different list of follow-up recommendations, and/or other input-receiving object. The input-receiving object can be a digital object that can be navigated to using an input device (e.g., mouse), or can be a physical object, such as a key with a fixed display, a key with a modifiable display, or other physical object.

[0072] As such, the system **200** can include and/or interface with a set of databases **230** (e.g., EHR, EMR, RIS, CIS, PACS, etc.). Additionally or alternatively, the system can include and/or interface with: a reporting platform **140**; a Picture Archiving and Communication System (PACS) and/or alternative image viewing and image storage platform; a speech recognition platform; a radiology worklist; a Radiology Information System (RIS); an electronic medical record (EMR) database; an electronic health record (EHR) database; a Clinical Information System (CIS) platform; a Health Information System (HIS) platform; a Laboratory Information System (LIS) platform; vendor-neutral archive (VNA) components; ontologies (e.g., radiological or other clinical ontology database); and/or any other database, storage, server, and/or software tools.

[0073] In a specific example, the system includes a reporting platform **240** (including a speech recognition platform and a user interface), wherein the reporting platform receives inputs and/or user actions from a radiologist, and displays a generated radiology report (e.g., determined using one or more models). In variants, the reporting platform **240** can include an input interface **241** (e.g., touch screen, keyboard, mouse, button, key, microphone, text box, touch input device, sound input device, optical sensor, etc.) as a component of user interface **235**, which can function to receive input from a user, a speech transcription platform **242**, and/or any other suitable components. The input interface can be rendered at a display of a user device (e.g., as shown in FIGS. **15**A and **15**B), part of an audio input device (e.g., the user device, microphone associated with speech-to-text software, etc.), include any combination of devices, and/or include any other device(s). In embodiments, the interface **235** can be configured for single-input approval of a follow-up recommendation responsive to a finding summary generated from a radiology report for a patient, using input interface **241**, where the input can be a single click, single button press or other single input.

[0074] In examples, the user device can include: a computer (e.g. a radiologist workstation computer), a headset (e.g., a virtual reality (VR) headset, an augmented reality (AR) headset, etc.), a mobile device (e.g., smartphone), and/or any other suitable device. Components of a user device can include a display subsystem (e.g., monitor, screen, projected image, etc.), an input subsystem (e.g., keys, touchscreen, microphone, etc.), one or more sensors (e.g., inertial measurement units, accelerometers, gyroscope, cameras, etc.), a processing subsystem, and/or any other suitable subsystem. Optionally, the system can include and/or interface with a software development kit, wherein customers and/or third parties can build additional features (e.g., further tools, features, functionality, analytics, historical report search, etc.) on top of the system (e.g., the reporting platform). The system **200** can include and/or interface with an optional reporting platform.

[0075] The reporting platform **240** can optionally include a virtual assistant **243** (e.g., chat bot, voice-based assistant, etc.), which can function to provide information to and/or receive information from a user. In variants, the virtual assistant can receive input from a user and determine an appropriate response. In examples, the virtual assistant can respond by: answering a user question, directing the user to information (e.g., contained within the report, linked to outside of the report, etc.), update an error within the generated report, and/or otherwise function. Additionally or alternatively, the virtual assistant **243** can determine a set of information to surface to and/or solicit from a user. In examples, the virtual assistant can surface information (e.g., via a notification) to a user, such as: an indication that an error has been corrected, a section of a report that requires further review, contact information of another medical professional (e.g., on the patient's care team, a specialist, a clinical trial coordinator, etc.) and/or any other entity (e.g., patient emergency contact information), and/or any other suitable information. In further examples, the virtual assistant can prompt a user to provide an input (e.g., as a response to information surfaced to the user), which can include a direct input to the report (e.g., fill out an incomplete section of a report), an input required for one or more models to run (e.g., to fill out an incomplete section of a report, to perform an error correction, etc.), a selection (e.g., a positive or a negative selection, a selection from a plurality of options, etc.) of one or more model outputs (e.g., a verification/rejection of an error correction performed by the system, a dropdown menu selection, etc.), and/or any other suitable input. Additionally or alternatively to a reporting platform, the system (e.g., the set of trained models) can integrate directly with one or more external systems (e.g., RIS, PACS, HER, etc.), wherein the system can output a radiology report with minimal or no input from a radiologist.

[0076] The system **200** can optionally further include and/or interface with a radiology platform (e.g., radiology reporting platform, PowerScribe, Fluency for Imaging, etc.), wherein the radiology platform can include a speech recognition system which is equivalently referred to herein as any or all of: a speech recognition platform, a speech transcription system and/or platform, a voice recognition system and/or platform, a voice transcription system and/or platform, a speech-to-text system and/or platform, and/or any other suitable platform including any suitable tools and/or programs. Additionally or alternatively, the radiology platform can include and/or interface with any other software tools and/or programs; interfaces (e.g., set of worklists); and/or any other tools or components.

[0077] In a first variant, the system can include and/or be configured to interface with a reporting platform (e.g., including a voice recognition platform). In a first example, a radiology report can be (partially) populated with text based on findings and/or associated information (finding characteristics, findings classifications, etc.) determined using a set of models. In a first specific example, a finding classification can be determined based on a finding identified in the radiology report (e.g., manually dictated or typed), and inserted into the radiology report. In a second specific example, a finding classification can be determined based on one or more sets of radiology images, and inserted into the radiology report (e.g., automatically inserted prior to the radiologist manually editing the report, inserted in response to a user action, etc.). An example is shown in FIG. **9**B. The inserted text can optionally be customized and/or modified by a radiologist. In an illustrative example, the radiologist can specify whether modifiers (e.g., “S”) are included in findings classifications, how the findings classifications are formatted, whether a mostly negative study is in a first classification or a second classification (e.g., Lung-RADS 1 or Lung-RADS 2; BI-RADS 1 or BI-RADS 2; etc.), and/or any other parameter adjustments. In a second example, patient information (e.g., patient information relevant for the current radiology report) can be displayed for a radiologist editing the radiology report. In examples, the system can display a dashboard, side panel, flag, notification, reminder of pertinent information (e.g., findings) that the radiologist should address on the current examination, and/or any other patient information display. The radiologist can optionally perform a user action (e.g., hotkey press) to insert one or more components of the displayed patient information (e.g., a finding classification, finding characteristics, etc.) into the radiology report. In a third example, a notification can be provided to the radiologist when a first finding classification (e.g., dictated or typed by the radiologist) conflicts with a second finding classification determined based on one or more sets of radiology images, wherein the radiologist can optionally select one of the first or second classification (e.g., replacing the first finding classification with the second finding classification in response to a user action). In a specific example, the notification can include the second classification (e.g., the correct classification) and/or an explanation of why the finding corresponds to the second classification (e.g., finding characteristics determined from the set(s) of radiology images such as nodule size, nodule number, nodule changes across exams, etc.). An example is shown in FIG. **9**A.

[0078] In a second variant, the system can include and/or be configured to interface with a patient management program and/or patient tracking program. Examples are shown in FIG. **13**A and FIG. **13**B. For example, the system can function to track patient information, determine and/or initiate scheduling (e.g., scheduling follow-up exams), determine and/or initiate communications (e.g., with a patient, with a provider, with an insurance company, etc.), determine and/or initiate referrals, and/or otherwise manage patients. In a first example, the system can function to track patients and/or initiate communications associated with radiology findings, laboratory findings, pathology results, vital signs, and/or other patient information. In an illustrative example, if a patient has a high creatinine and/or blood glucose level in the ER, the system can automatically initiate a follow-up with a specialist to exclude renal disease or diabetes. In another illustrative example, if a patient's pathology biopsy or cytology results return for potential cancer (i.e., positive), the patient can be automatically referred to an oncologist for treatment planning. In another illustrative example, if a patient has a high blood pressure in the ER, the system can automatically initiate a follow-up and/or tracking to assess for hypertension and its various causes. In a second example, the system can include and/or be configured to interface with a screening program (e.g., a cancer screening program) and/or screening study. Examples of screening programs and/or associated screening exams include: lung cancer screening (e.g., LDCT), breast cancer screening (e.g., mammography), colonoscopies, bone density testing, heart disease, abdominal aortic aneurysms, high blood pressure, diabetes or pre-diabetes, skin cancer screening, and/or any other screening.

The screening program can optionally be associated with one or more facilities. Patient associated with (e.g., enrolled in) the screening program can optionally be patients associated with one or more diseases (e.g., lung cancer, breast cancer, etc.).

[0079] In a first embodiment, the system can function to identify patients to enroll in a screening program (e.g., either regularly or for a one-time screening). For example, one or more patients (associated with a facility) with patient information satisfying a set of eligibility criteria can be identified, recommended to the screening program, and/or optionally automatically enrolled in the screening program. Eligibility criteria can be determined based on consensus guidelines, risk factors (e.g., smoking history, family history, age, COPD, etc.), patient information (e.g., demographic information, clinical history, laboratory and/or pathology results, patient vitals, findings, finding classifications, impressions, etc.), and/or other information. An illustrative example of eligibility criteria includes: greater than a threshold number of pack-years (e.g., at least 20 pack-years), age thresholds (e.g., between 50 and 80), smoking history thresholds (e.g., currently smoke or quit within the last 15 years), a combination thereof, and/or any other eligibility criteria.

[0080] In a second embodiment, the system can function to track patients enrolled in the screening program (e.g., tracking: findings, finding characteristics, finding classifications, recommendations, exam scheduling/ordering information, other patient information, etc.). For example, tracking can include (iteratively over time, for each of a set of radiology reports): processing a radiology report to determine a finding classification (e.g., screening the patient for a disease), and updating patient information (e.g., the finding classification, associated recommendations, etc.) based on the finding classification. In a specific example, follow-up recommendations are (automatically) determined based on the finding classification and consensus guidelines. In an illustrative example, longitudinal Lung-RADS category progression for a patient is tracked.

[0081] In a third embodiment, the system can function to flag patients enrolled in the screening program. Flagging a patient can include outputting a notification (e.g., alert), displaying an indicator (e.g., on a dashboard), updating patient information, and/or performing any other suitable actions. The patient is preferably flagged to a user (e.g., a navigator of the screening program), but can be otherwise flagged. In a first example, a patient is flagged when a schedule for an exam does not meet a set of scheduling criteria (e.g., based on the finding classification, recommendations, insurance guidelines, a scheduling due date, etc.). In an illustrative example, a patient who has a one-year follow-up recommendation for a Lung-RADS 1 or 2 is flagged if a follow-up exam is scheduled less than one year after their previous exam. Examples are shown in FIG. **10** and FIG. **12**A. In a second example, a patient is flagged when the associated patient information does not meet a set of eligibility criteria. Examples are shown in FIG. **10** and FIG. **12**B.

[0082] In a fourth embodiment, the system can function to flag a radiology report and/or associated information (e.g., when an incorrect finding classification has been documented in the radiology report). For example, a notification and/or other flag can be outputted when a finding classification determined based on the radiology report does not match a finding classification determined based on an associated set of radiology images. An example is shown in FIG. **8**. In a specific example, a radiology report (e.g., a completed radiology report) can be processed using a first set of models to determine a first classification for a finding (e.g., to identify a Lung-RADS category manually inputted by a radiologist), and one or more sets of radiology images associated with the radiology report can be processed using a second set of models to determine a second classification for the finding (e.g., to identify a Lung-RADS category using image analysis). The second set of models can optionally determine the second classification by determining finding characteristics for one or more sets of radiology images, and determining the second classification based on the finding characteristics. Additionally or alternatively, a single set of models (e.g., a multimodal model) can process the radiology report and the one or more sets of radiology images to determine and/or compare the first and second classifications for the finding. One or more actions can be performed based on a comparison between the first classification and the second classification (e.g., when the classifications do not match), including: outputting a notification to a user, receiving a user selection (of the first classification or the second classification), updating patient information (e.g., updating recommendations for the patient corresponding to the classification selected by the user, adjusting the radiology report, etc.), and/or any other suitable actions. In a specific example, the notification can include the second classification (e.g., the correct classification) and/or an explanation of why the finding corresponds to the second classification (e.g., finding characteristics determined from the set(s) of radiology images such as nodule size, nodule number, nodule changes across exams, etc.). Processing the radiology report (to determine the first finding classification) and processing the set(s) of radiology images (to determine the second finding classification) can be performed: in parallel (e.g., contemporaneously), sequentially (e.g., the second classification is determined in response to detecting a finding such as a Lung-RADS finding in the radiology report; the second classification is determined before the radiologist completes the radiology report; the second classification is determined after the first classification is determined from the radiology report; etc.), and/or at any other time.

[0083] However, the system can otherwise be and/or interface with a screening program and/or any other patient management or tracking program.

[0084] In a third variant, the system can include and/or be configured to interface with a user device and/or patient viewing platform. For example, the system can function to provide an adjusted radiology report to the patient via the user device and/or patient platform. An example is shown in FIGS. **11** and **15**A-**15**B. In an illustrative example, supplemental text (e.g., term glossary, resources, translated text, other supplemental information, etc.) can be determined for the radiology report; the radiology report can be adjusted based on the supplemental text (e.g., the supplemental text supplements and/or replaces text in the radiology report) or using a transformer model (e.g., GPT, etc.); and the adjusted radiology report can be provided to the patient. In a first specific example, all or a portion of a radiology report can be translated to language more easily understood by patients (e.g., 6th-grade reading level, 8th-grade reading level, etc.) and/or a different language. In a second specific example, the radiology report can be supplemented with an associated glossary of terms used in the report. In a third specific example, the patient can be provided patient resources and/or links to patient communities related to the disease(s) described in the report.

[0085] However, the system can otherwise be and/or interface with one or more systems.

[0086] The system **200** can optionally be tailored to the preferences of a particular radiology group, tailored to the preferences of multiple radiology groups, agnostic of radiology group preferences, tailored to the preferences of an individual radiologist and/or aggregated set of radiologists, tailored to the preferences of a PCP and/or patient, tailored to the preferences of a manager or other healthcare facility entity (e.g., nurse navigator reviewing the radiology worklist(s)), and/or otherwise configured.

[0087] In a preferred set of variations, the system **200** is configured to interface with (e.g., integrate with, communicate with, be built on top of, as a virtual machine, etc.) a radiology platform including a speech recognition platform, wherein the method S**200** is adapted to integrate with the features of the particular radiology platform.

[0088] Additionally or alternatively, the system **200** can be otherwise suitably configured and/or include any other components.

4. Method

[0089] As shown in FIG. **1**, a method **100** for the computer-assisted implementation of radiology recommendations includes any or all of: receiving a set of inputs S**100**; determining and/or identifying a set of findings S**200**; determining a set of follow-up recommendations S**300**; and triggering an action based on the set of follow-up recommendations S**400**. Additionally or alternatively, the method **100** can include any other suitable processes performed in any suitable order.

[0090] The conventional process for handling follow-up recommendations, such as those associated with incidental findings, has many limitations, which can result in poor outcomes for the patient and the healthcare facility. In conventional workflows, the appropriate follow-up is often defined by consensus guidelines from a number of national clinical societies, though these can vary depending on the radiologist and the clinician's best judgments, as well as on the patient's specific circumstances and associated findings. However, even when the appropriate follow-up is recommended by the radiologist, it often turns out to be very difficult to ensure this follow-up is communicated to the physician responsible for the patient after discharge from the hospital, ensure the follow-up is communicated directly to the patient, and ensure the follow-up is performed according to the recommended timeline, per national consensus guidelines. As a result, many recommendations are not followed up on, which can lead to increased costs, damage to the patient, or even death.

[0091] The method **100** implements advanced models for performing one or more of: automatically extracting findings from radiology reports, generating summaries of findings, organizing findings (e.g., by category, by subcategory), rendering finding summaries at an interface of a radiology system, rendering follow-up recommendations pertaining to the finding summaries at the interface for review and approval by users of the interface, providing one or more objects at the interface by which users can efficiently approve and initiate execution of the follow-up recommendation(s), confirming completion of the follow-up recommendation(s), training the advanced model(s) to continuously improve efficiency by which follow-up recommendations are generated, training the advanced model(s) to continuously improve accuracy of finding summarizations by which follow-up recommendations are generated, training the advanced model(s) to continuously improve appropriateness of follow-up recommendations, and generating other relevant outputs.

[0092] The methods described include steps that significantly increase efficiency of systems used to execute follow-up actions and process radiology report backlogs, in relation to number of full time equivalent (FTE) personnel required to perform work (e.g., review findings from radiology reports, execute recommended follow-up actions to “close the loop” responsive to the finding(s) in the radiology report(s)). In examples, the methods and systems described can provide a novel interface by which a user (e.g., navigator) can be presented with finding summaries and approve execution of follow-up recommendations, in a manner that significantly reduces FTE numbers required to process a number of reports. As such, the inventions described can clear backlogs by executing follow-up recommendations in an unprecedented manner. In examples, the interface can reduce a number of full-time equivalent (FTE) users required to initiate execution of follow-up recommendations for a set of radiology reports by at least: 50%, 55%, 60%, 65%, 70%, 75%, 80%, 85%, 90%, 95%, 100%, or greater, depending upon institutional requirements and/or other factors.

[0093] The method **100** also preferably functions to enable incidental findings to be consistently and reliably handled, which can involve any or all of: ensuring that they are included in the radiology report; ensuring that a follow-up recommendation is provided based on the incidental finding(s); ensuring that the follow-up recommendations are implemented (e.g., at a current time, at a later time, etc.); and/or ensuring or providing any other outcomes. This can subsequently function to improve patient outcomes through promoting preventative care of the patient (e.g., preventing incidental findings from worsening), prevent missed revenue opportunities for healthcare facilities (e.g., from missed follow-up procedures), reduce healthcare facility liability due to missed follow-up, reduce a mental load of the radiologist and/or physicians in implementing incidental finding follow-up (e.g., by automating any or all of the processes involved in this); and/or perform any other functions. Additionally or alternatively, the method **100** can perform any other functions.

[0094] The method **100** is preferably configured specifically for at least incidental findings, and further preferably significant incidental findings, but can additionally or alternatively be performed for non-incidental (e.g., standard, critical, etc.) findings and/or any other information provided in and/or associated with a radiology report.

[0095] Examples of incidental findings can include, for instance, but are not limited to, any or all of: pulmonary nodules, persistent opacities, aortic aneurysms, coronary artery calcification, cystic and solid lesions and/or masses in a wide range of organ systems, lytic and blastic lesions (e.g., in the spine), prominent lymph nodes, mural thrombus, dilated biliary ducts, tumors, or any other findings.

[0096] The method **100** is preferably performed with a system including one or more computing subsystems configured to process and/or access information, such as radiology images (e.g., scans from a study), radiology reports, patient information (e.g., medical records, medical history, demographic information, associated clinicians such as primary care physician, etc.), healthcare facility information (e.g., on-call physicians, physician contact information, procedure scheduling information, etc.), and/or any other suitable information, such as, but not limited to, a system **200** as described above. The one or computing subsystems can be remote (e.g., cloud-based), local (e.g., at a healthcare facility server), distributed among multiple devices, and/or any combination. Additionally or alternatively, the system can include any other suitable components and/or the method can be performed with any suitable system.

4.1 Method—Receiving a Set of Inputs S**100**

[0097] The method **100** can optionally include receiving a set of inputs S**100**, which functions to receive information with which to perform any or all other processes of the method **100**.

[0098] S**100** is preferably performed initially during the method **100**, but can additionally or alternatively be performed during and/or after another process of the method **100**, multiple times during the method **100**, in response to a trigger (e.g., request from a user, determination of particular incidental finding and/or follow-up recommendation, etc.), and/or at any other times.

[0099] The set of inputs preferably includes a radiology report, which can be completed, partially completed, or any combination. The radiology report can be manually generated (e.g., by a radiologist), automatically generated (e.g., with a trained model), a combination of manually and automatically generated (e.g., report which is manually generated aside from an automatically generated impression section), and/or otherwise suitably generated.

[0100] The set of inputs can additionally or alternatively include a set of images associated with a scan and/or study of the patient, where the method includes and/or interfaces with a process which automatically determines a set of findings (e.g., incidental findings) associated with the patient based on the set of images (e.g., with a trained model).

[0101] The set of inputs can optionally additionally or alternatively include supplementary information, such as that associated with the patient (e.g., prior studies corresponding to the same incidental finding, prior follow-up recommendations, historical information, other patient information, etc.), that associated with other patients (e.g., data associated with an aggregated set of patients, etc.), that associated with another user (e.g., radiologist preferences, PCP preferences, radiologist group preferences, etc.), that associated with radiologist consensus guidelines and/or best practices (e.g., for use in creating a lookup table, for use in training a model to automatically determine follow-up recommendations, etc.), and/or any other information.

[0102] In a first set of variations, the set of inputs includes a radiology report which is manually generated by a radiologist (e.g., with speech recognition/dictation software, typed, written, etc.). Additionally, the set of inputs can include any other information.

[0103] In a second set of variations, the set of inputs includes a radiology report in which one or more sections is automatically generated (e.g., with a set of trained models). Additionally, the set of inputs can include any other information. In a set of specific examples, for instance, the radiology report includes a report in which an impression section is automatically generated with a set of models as described in U.S. application Ser. No. 17/020,593, filed 14 Sep. 2020, which is incorporated in its entirety by this reference.

[0104] In a third set of variations, the set of inputs includes a set of images, which are automatically processed in order to determine a set of incidental findings and/or a set of follow-up

recommendations (and optionally generate any or all of the radiology report).
[0105] Additionally or alternatively, S**100** can include any other suitable processes.
4.2 Method—Determining and/or Identifying a Set of Findings S**200**
[0106] The method **100** can optionally include determining and/or identifying a set of findings S**200**, which functions to identify findings with which to prompt and/or perform the subsequent processes of the method **100**. Additionally or alternatively, S**200** can function to perform any or all of: identifying incidental findings in particular and/or distinguishing incidental findings from non-incidental findings and/or other information; identifying significant incidental findings (e.g., incidental findings associated with a follow-up recommendation and/or advised to include a follow-up recommendation) and/or distinguishing incidental findings from insignificant incidental findings; characterizing (e.g., classifying) an incidental finding as a particular type of incidental finding; detecting that one or more incidental findings is missing from the radiology report; and/or any other functions.
[0107] S**200** is preferably performed in response to and/or based on S**100**, but can additionally or alternatively be performed in absence of S**100** (e.g., initially in the method S**200**), in response to one or more processes of the method S**200**, in parallel with and/or at least partially overlapping with another process of the method S**200**, in response to a trigger, multiple times during the method S**200** (e.g., at a predetermined frequency, continuously, etc.), and/or at any other times and/or combination of times.
[0108] S**200** is preferably performed at least partially automatically and further preferably without any manual user (e.g., radiologist, patient, etc.) input and/or actions, but can optionally additionally or alternatively be performed partially of fully with manual input.
[0109] The set of findings identified in S**200** preferably includes incidental findings, further preferably clinically significant incidental findings (e.g., associated follow-up and/or a follow-up recommendation), but can additionally or alternatively include clinically insignificant findings, non-incidental findings (e.g., normal findings, abnormal findings, etc.), and/or any other information.
[0110] Identifying the set of findings (e.g., only incidental findings, all findings, etc.) can include any or all of: identifying the findings based on the images in a radiology study; identifying the radiologist's inclusion of an incidental finding or other finding in a radiology report (e.g., in the “findings section”); characterizing, classifying, and/or distinguishing different types of findings; and/or can include any other suitable processes for identifying an incidental finding or any other finding. Additionally or alternatively, S**200** can include identifying any other information in a radiology report and/or any other information associated with incidental findings. For instance, S**200** can include identifying follow-up recommendations associated with an incidental finding for a report in which the radiologist did include a follow-up recommendation for the incidental finding.
[0111] S**200** is preferably performed at least partially automatically, such as with one or more trained models (e.g., machine learning models, deep learning models, neural networks, etc.). In preferred variations, for instance, a set of trained models can be used to perform any or all of: determining incidental findings based on radiology images, characterizing incidental findings (e.g., as critical vs. non-critical, as significant vs. not significant, versus non-incidental findings, etc.), checking for the presence of and/or identifying incidental findings in a radiology report, and/or performing any other processes. The trained models are preferably machine learning models (e.g., deep learning models, neural networks, regression models, reinforcement learning models, inverse reinforcement learning models, etc.). Additionally or alternatively, untrained models and/or algorithms (e.g., rule-based, programmed, etc.), lookup tables and/or databases, human input, and/or any other suitable tools can be used for any or all of these processes.
[0112] In a preferred set of variations, S**200** includes processing a radiology report (e.g., a typed radiology report, the audio of a dictated radiology report, a written radiology report, etc.) received in S**100** with a set of one or more trained models to detect the presence of language (e.g., words,

key words, phrases, etc.) which corresponds to (e.g., is predicted to correspond to) a set of findings. The trained model(s) preferably includes a neural network, and further preferably a neural network configured for NLP (e.g., a trained transformer model), such as a neural network configured to detect language (e.g., words, phrases, etc.) associated with pathologies typically corresponding to a desired category of findings (e.g., incidental findings) and/or any other language corresponding to the desired categories of findings. In a first specific example, S**200** further includes identifying a particular section (e.g., findings section) in which the findings are most likely to be described, and then processing that particular section to detect if and/or which findings might be present. In a second specific example, S**200** is performed in absence of detecting a particular section (e.g., processes multiple sections of the report, processes all sections of the report, etc.).

[0113] S**200** further preferably includes processing any or all of the outputs of the trained models and/or algorithms with rule-based logic (and/or any other programmed processes). In some variations, for instance, upon detecting that a portion of the radiology report (e.g., text, string of text, sentence, sentences, phrase, set of words, etc.) is associated with (and/or predicted to be associated with) a finding and/or a particular type of finding (e.g., incidental finding), rule-based logic can be implemented to determine a set of features associated with that text, where the set of features preferably functions to determine if a follow-up recommendation is needed (and/or what type of follow-up recommendation is needed). The features can include, for instance, any or all of the following features associated with a finding (e.g., a pathology associated with the finding): size parameters (e.g., volume, length, width, depth/thickness, diameter, etc.); shape parameters (e.g., regular, irregular, circular, elongated, ovoid, etc.); quantity parameters (e.g., a number of detected polyps); location parameters (e.g., relative to anatomical landmarks, relative to an area of concern, etc.); and/or any other parameters. These can be detected/determined based on any or all of: keywords associated with these features (e.g., “size,” “diameter,” “millimeters,” “milliliters,” “circular,” “irregular,” “symmetric,” “one,” “two,” “single,” “multiple,” “proximal,” “distal,” etc.); the detection of numbers (e.g., as opposed to words); the proximity of feature words to other words of the sentence; and/or the features can be detected in any other way(s) (e.g., with the trained models). Alternatively, S**200** can be performed in absence of detecting any or all of these features.

[0114] Rule-based logic can additionally or alternatively be used to determine contextual features associated with the findings and/or features of the findings, which can function to determine if any or all of the features (and/or findings) are negated (e.g., in order to not prompt one or more follow-up recommendations, in order to select appropriate follow-up recommendations, in order to finalize the set of incidental findings which are present, etc.). In a set of examples, for instance, determining the contextual features includes checking for a set of negation words (e.g., predetermined negation words such as “not,” “no,” etc.) proximal to the features and/or findings (e.g., within the same sentence, immediately prior to, etc.), but can additionally or alternatively include any other processes. Additionally or alternatively, contextual features can be determined with another process (e.g., with a trained model), S**200** can be performed in absence of determining contextual features, and/or S**200** can include any other processes.

[0115] S**200** can optionally additionally or alternatively include characterizing (e.g., classifying) any or all of the detected findings (e.g., incidental findings), such as by assigning any or all of the detected findings to one or more categories, such as categories which correspond to (e.g., map to) a particular type of finding; a particular class and/or type of recommendation (e.g., based on radiology consensus guidelines, best practices, predetermined associations, etc.); a finding classification, and/or any other categories. Characterizing the findings can be performed with any or all of: a decision tree or other rule-based process, lookup table, equation and/or formula and/or algorithm, model, and/or any other tools.

[0116] Additionally or alternatively, S**200** can process the set of inputs with only programmed/rule-based processes, only with trained processes, and/or with any other processes or combination of processes.

[0117] In identifying an incidental finding, S**200** can optionally include characterizing the incidental finding into a set of classes and/or groupings of incidental findings. The set of classes preferably functions to inform subsequent processes of the method, such as which follow-up is most suitable, which actions should be triggered based on the incidental finding, but can additionally or alternatively be used in any other suitable ways. The set of classes can be determined based on any or all of: the finding itself (e.g., type of incidental finding, body region, associated condition, etc.), other findings (e.g., comorbidities, etc.), the radiology report (e.g., whether the radiologist noted the incidental finding, whether the radiologist did not note the incidental finding, whether the recommendations section includes follow-up associated with the incidental finding, whether the recommendations section does not include follow-up associated with the incidental finding, etc.), patient information (e.g., historical information, prior radiology reports, demographic information, pre-existing conditions, etc.), healthcare facility information (e.g., availability/ability to perform follow-up), physician information (e.g., which physicians the patient is under the care of), an identifier of the incidental finding (e.g., human radiologist, model and/or algorithm, etc.), consensus guidelines (e.g., dictating appropriate and/or recommended follow-up for an incidental finding), and/or any other suitable information. Additionally or alternatively, any or all of the classes described below can correspond to scenarios which the method **100** is configured to detect and/or be configured to perform within.
[0118] The set of classes can optionally include a first class (Class I) indicating that one or more incidental findings were identified by a radiologist in the radiology report and that accurate consensus guideline recommendations were provided by the in the radiology report. In specific examples, for instance, this class can indicate that the recommendations can be relayed in S**400** to the patient's outpatient physician(s), to the patient, and also tracked for future follow-up, and can optionally indicate that S**300** can be skipped. Additionally or alternatively, the class can be used in any other suitable ways.
[0119] The set of classes can optionally additionally or alternatively include a second class (Class II) indicating that one or more incidental findings were identified by a radiologist in the radiology report, but that recommendations associated with the incidental findings were not clearly provided. In specific examples, this can function to trigger the performance of S**300** (e.g., after the radiologist has finished the report, while the radiologist is still working on the report, independent of the report's completion, etc.), wherein the recommendations can be determined any or all of: automatically (e.g., with one or more trained models), by a radiologist (e.g., the radiologist completing the report, a different radiologist, etc.), or any combination. In a first specific example of Class II characterization, the method can include determining that missing recommendations need to be identified, and in response, re-introducing the study back into the radiologist's queue for review, such as with a label or tag point the radiologist to the incidental finding. Once the radiologist adds the recommendation (e.g., in a report addendum including the recommendation), it can be used to trigger one or more actions in S**400**, such as being provided to the patient's outpatient physician(s), to the patient, and/or tracked for future follow-up. In a second specific example, missing recommendations can be identified automatically and indicated to the radiologist before the radiologist finalizes his or her report dictation, so that the radiologist can include the recommendation prior to signing the report. Additionally or alternatively, Class II incidental findings can be otherwise characterized and/or used.
[0120] The set of classes can optionally additionally or alternatively include a third class (Class III) indicating that incidental findings were missed by the radiologist in the report. This can be identified, for instance, automatically with a set of trained models (e.g., machine learning models) review the radiology images and flag significant incidental findings that need follow-up (e.g., based on consensus guideline criteria). In specific examples, the study can optionally be added back to the radiologist queue for review, as indicated for instance with a tag and/or label. In an event that the radiologist confirms that this is a significant incidental finding, he or she can add the incidental

finding and an associated recommendation to the report (e.g., in a report addendum to the recommendations section). In a second specific example, one or more trained models can review the images and flag significant incidental findings immediately after study image acquisition, so that any missed incidental findings can be brought to the radiologist's attention before the radiologist finalizes his or her report dictation. Additionally or alternatively, the recommendations can be automatically determined (e.g., in S**300**), and/or Class III incidental findings can be otherwise characterized and/or used. As such, S**200** can include: determining that at least one of the set of classifications/classes indicates a missed incidental finding that was missed by a radiologist generating a radiology report, and, through at least one of a RIS and an embodiment, variation, or example of the interface described, returning the radiology report to a queue of the radiologist in response to the missed incidental finding.

[0121] In the specific example shown in FIG. **3**, a decision tree can be used in assigning one of a set of classes to the radiology report.

[0122] Additionally or alternatively, the incidental findings can be characterized into any other suitable classes and/or combination of classes.

[0123] Further additionally or alternatively, characterizing the incidental findings can include comparing an incidental finding with a set of criteria and/or thresholds (e.g., criteria indicating whether or not a follow-up recommendation should be made) and/or any other suitable processes.

[0124] S**200** can additionally or alternatively include any other suitable processes.

4.2 Method—Determining a Set of Follow-Up Recommendations S**300**

[0125] The method **100** can include determining a set of follow-up recommendations S**300**, which functions to identify and/or formulate a set of follow-up recommendations associated with any or all of a set of findings (e.g., incidental findings) (e.g., as determined in S**200**). Additionally or alternatively, S**300** can function to automatically locate the set of follow-up recommendations within a radiology report; identify that one or more follow-up recommendations is missing and/or incomplete; create and/or complete one or more follow-up recommendations; identify a mismatch between the set of findings and the set of follow-up recommendations; and/or perform any other functions. In examples, follow-up recommendations can be structured to adhere to institution requirements, clinical indication protocols and requirements, consensus guidelines and best practices, and/or other suitable boundary conditions.

[0126] Any or all of S**300** can optionally be performed in response to S**200**, such as based on the set of findings determined in S**200**. Any or all of S**300** can optionally additionally or alternatively be performed in absence of S**200**, such as without identifying and/or without first identifying any or all of a set of findings. Further additionally or alternatively, any or all of S**300** can performed prior to S**200**, as part of S**200** (e.g., in classifying the set of incidental findings), as part of S**400**, multiple times (e.g., continuously, at a predetermined frequency, at a random set of intervals, in response to a trigger, etc.), and/or at any other suitable times. Additionally or alternatively, the method **100** can be performed in absence of S**300**.

[0127] S**300** is preferably at least partially performed automatically, such as with a set of trained models and/or algorithms. Additionally or alternatively, any or all of S**300** can be performed with rule-based logic and/or algorithms, or can otherwise be suitably performed.

[0128] In variations in which S**200** includes classifying one or more incidental findings, S**300** is further preferably performed in response to the classification. Additionally or alternatively, S**300** can be performed in absence of a classification, and/or at any other time(s).

[0129] The follow-up recommendations preferably include those which corresponding to an incidental finding, but can additionally or alternatively include follow-up recommendations corresponding to another finding (e.g., associated with the primary reason for the study), all findings (e.g., to be distinguished later), and/or any combination of findings.

[0130] In a preferred set of variations, S**300** is configured to detect and track follow-up recommendations for only incidental findings and/or a subset of incidental findings (e.g.,

significant incidental findings), as findings associated with the primary reason for the study will be already handled and/or appropriately followed up on according to existing procedures and/or protocols.
[0131] In a second set of variations, all follow-up recommendations are determined and/or tracked in S**300**.
[0132] Determining the set of follow-up recommendations can include, for instance, any or all of: checking for and/or locating existing follow-up recommendations within a radiology report; verifying that one or more follow-up recommendations are associated with an incidental finding (e.g., critical incidental finding); verifying that each incidental finding is either associated with a follow-up recommendation or that no follow-up recommendation is required; selecting and/or formulating one or more follow-up recommendations; flagging a radiology report for review and insertion of follow-up recommendations by a radiologist (e.g., based on a Class II classification, based on a Class III classification, etc.); and/or any other suitable processes.
[0133] S**300** is preferably at least partially performed with a set of trained models (e.g., machine learning models, deep learning models, neural networks, NLP models, trained transformer models, etc.), which can individually and/or collectively function to detect recommendations within the radiology report. This can additionally function to detect recommendations from anywhere within a report, such as in cases in which recommendations are not necessarily delegated to particular sections or locations within a report. Additionally or alternatively, the set of trained models can be used for any other processes (e.g., as described below), such as, but not limited to: generating recommendations, completing recommendations, classifying recommendation, selecting and/or triggering an output/action based on the recommendation(s), and/or any other processes.
[0134] Additionally or alternatively, any or all of S**300** can be performed with a set of rule-based and/or programmed processes (e.g., rule-based logic, decision trees, etc.), manual processes, any other processes, and/or any combination of processes.
[0135] The set of trained models is preferably configured to process language (e.g., typed text, written text, dictated speech, etc.) in the radiology report (e.g., as described above), but can additionally or alternatively be configured for image-based processing and/or any other types of processing. The set of trained models further preferably includes one or more neural networks (e.g., NLP neural networks, trained transformer model, etc.) configured to detect different types of entities in the radiology report, such as: keywords, contextual language (e.g., in surrounding text), a combination of keywords and contextual language, features, and/or any other information. Additionally or alternatively, any or all of the language processing can be performed with rule-based and/or programmed processes, a combination of processes, and/or any other processes.
[0136] S**300** can optionally include checking for and/or locating a set of follow-up recommendations S**310**, which functions to determine which follow-up recommendations are associated with the radiology report, and can additionally function to trigger the appropriate outputs and/or actions in S**400**, detect if any follow-up recommendations are missing, and/or can perform any other functions. S**310** (and/or any other processes of S**300**) is preferably at least partially performed with a set of trained models (e.g., as described below, as described above, etc.), but can additionally or alternatively be performed with one or more programmed and/or rule-based processes (e.g., as described below, as described above, etc.), and/or with any other processes.
[0137] S**300** can optionally additionally or alternatively include characterizing any or all of a set of follow-up recommendations S**320**, which functions to inform any or all of the remaining processes of the method **100**.
[0138] In a set of variations, any or all of the radiology report is processed with a transformer-based model that works at the sentence level, which characterizes (e.g., classifies) individual sentences. The characterization preferably indicates whether or not the sentence (or other text structure/amount) corresponds to a follow-up recommendation, but can additionally or alternatively determine (e.g., specify) a type of recommendation (e.g., follow-up imaging, examination,

specialist referral, bloodwork, etc.) associated with the sentence; a particular finding and/or type of finding (e.g., incidental finding classification, significant incidental finding classification, particular finding classification, etc.); a feature associated with the follow-up recommendation and/or finding; a level of completion associated with the recommendation; and/or any other characterization(s).

[0139] The set of models (e.g., transformer-based model, other model(s), etc.) can further optionally process neighboring text (e.g., prior sentence(s), subsequent sentence(s), text within the sentence, other paragraphs, other sections, etc.) to determine an overall context associated with the sentence, which can be used to refine the individual sentence characterizations (e.g., to match the overall context). In specific examples, for instance, if it is unclear from an individual sentence what a characterization (e.g., classification) might be (e.g., based on an uncertainty calculation exceeding a predetermined threshold, based on a confidence metric falling below a predetermined threshold, etc.), an overall context (e.g., overall paragraph, neighboring sentences, whole report, etc.) can be determined to confirm, reject, alter, and/or otherwise examine the characterization. The context is preferably determined based on processing one or more sentences (or other strings of text) proximal to (e.g., immediately prior, immediately after, within a predetermined number of sentences within, etc.) a sentence and/or other string of text associated with a candidate recommendation, but can additionally or alternatively be located elsewhere in the radiology report and/or otherwise defined. Additionally or alternatively, a context can be determined with one or more rule-based processes, S**300** can be performed in absence of determining a context, and/or S**300** can be otherwise suitably performed.

[0140] The set of models (e.g., transformer-based model as described above, separate transformer-based model, transformer-based model with a text classifier, etc.) can further optionally function to determine one or more anatomical features (e.g., references to a particular anatomical feature) associated with the sentence(s) (or other text), which can function to determine, for instance, which body region(s) a recommendation and/or finding is associated with. In specific examples, for instance, determining an anatomical classification and/or set of features associated with the sentence can function to determine which anatomical region a recommendation and/or associated finding corresponds to (e.g., whether or not a detected nodule is associated with the liver versus the lung). Additionally or alternatively, S**300** can be performed in absence of detecting anatomical features; anatomical features can be detected during S**200** and/or with another process (e.g., processing other sections of the radiology report, processing patient and/or study metadata, etc.) of the method; and/or anatomical features can be determined in any other way(s).

[0141] S**300** further preferably includes a set of rule-based and/or programmed processes (e.g., implementing rule-based and/or hard-coded logic, etc.), which can function to determine a set of features associated with the detected recommendations. The set of features preferably includes a particular finding (e.g., which pathology, incidental finding, etc.) that the recommendation corresponds to. This can be used, for instance, to determine if any or all of the findings determined in S**200** are missing a recommendation, to determine an optimal and/or accurate set of actions/outputs to be triggered in S**400**, and/or can perform any other functions.

[0142] Additionally or alternatively, the set of features can include any or all of: a set of temporal features associated with the recommendation (e.g., time frame in which the follow-up recommendation should be performed); a type of recommendation (e.g., a recommended scan such as a CT scan, bloodwork, a specialist appointment, an examination, etc.); and/or any other recommendation features. These can be used, for instance, to produce a structured output which can be used downstream in determining and/or scheduling any or all of the actions and/or outputs in S**400**.

[0143] In a set of examples, for instance, S**300** includes detecting (e.g., with hard-coded, rule-based logic; with trained models; with decision trees; etc.) one or more temporal features associated with the follow-up recommendation, such as a timeline prescribed for a follow-up action. This is preferably determined based on the detection of one or more temporal keywords (e.g., “months,” “days,” “weeks,” “before,” “after,” a month name, a date, a year, etc.) and/or phrases, but can additionally or alternatively be determined based on other information, with a trained model, and/or with any other tools.

[0144] In another set of examples, S**300** includes detecting a type of follow-up (e.g., type of action and/or next step) associated with a recommendation and/or distinguishing between types of follow-up, such as detecting a recommendation for any or all of: further imaging, an examination (e.g., with a PCP, with a specialist, etc.), laboratory work, a procedure, and/or any other follow-up. The type of follow-up can be determined with any or all of: the detection of one or more keywords (e.g., “imaging,” “MRI,” “CT,” “lab work,” “lab,” “bloodwork,” “appointment,” “exam,” “procedure,” surgery,” etc.) and/or phrases; a trained model; and/or with any other tools.

[0145] Additionally or alternatively, S**300** can optionally include detecting a level of completion associated with any or all of the set of follow-up recommendations S**330**, which functions to ensure that accurate and comprehensive follow-up actions/outputs are triggered in S**400**. This can optionally additionally include detecting that one or more follow-up recommendations is missing from a radiology report. In some variations, for instance, S**330** includes determining whether or not a recommendation is complete and optionally further determining which components are missing from an incomplete recommendation. This is preferably performed with a rule-based and/programmed process, such as rule-based logic which identifies if and/or what components are missing from the recommendation itself (e.g., based on referencing consensus guidelines, a lookup table, a predetermined set of recommendation components, a decision tree, etc.) and if they are missing, S**300** can optionally include processing contextual information (e.g., other sections of the radiology report) to find and/or infer the missing information. Additionally or alternatively, S**300** can include referencing other information (e.g., consensus guidelines, a corpus of previously generated radiology reports, etc.) to detect that a recommendation is incomplete (and/or to complete the recommendation), and/or any other processes. In another set of variations, S**330** includes associating any or all of the set of follow-up recommendations with a corresponding finding, which can function to check for and/or confirm that each incidental finding in the report (e.g., as determined in S**200**) has an associated follow-up recommendation (if applicable).

[0146] In specific examples (e.g., as shown in FIG. **5**), this includes comparing the results of S**200** with follow-up recommendations detecting in S**300** (e.g., in S**310**, in S**320**, etc.) to determine if any follow-up recommendations are missing, if any follow-up recommendations do not have an associated incidental finding (e.g., for flagging the report, for further searching, for consolidation of follow-up recommendation, for removing redundancies in follow-up recommendations, etc.), if each of the follow-up recommendations is appropriate for the given finding, and/or if any other scenarios exist.

[0147] S**300** can optionally additionally include completing (e.g., automatically completing) any or all of the set of recommendations (e.g., incomplete recommendations) and/or generating (e.g., automatically generating) part or all of any or all of the set of recommendations S**340**, which can function to increase an accuracy and/or comprehensiveness of the outputs and/or actions triggered in S**400**; reduce a time and/or human effort required to complete a radiology report; and/or can perform any other functions. This is preferably performed automatically (e.g., by referencing a lookup table, by implementing a trained model, etc.), but can additionally or alternatively be performed manually (e.g., by flagging a radiologist to complete and/or add the recommendation), and/or any combination. Completing and/or generating a recommendation can be performed with any or all of: rule-based and/or programmed processes (e.g., referencing a lookup table, implementing hard-coded logic, processing a decision tree, etc.); trained models (e.g., generating text with a machine learning model, etc.); one or more templates; any combination; and/or any other processes. The completed and/or generated (e.g., fully generated) recommendation is preferably determined in accordance with (e.g., based on) any or all of: radiology consensus guidelines (e.g., Fleischner guidelines), radiology group guidelines and/or conventions, best

practices, user and/or group and/or facility preferences, and/or any other information. In some variations, for instance, the type and/or content of any or all follow-up recommendations are determined in accordance with the preferences and guidelines of the associated radiology group.
[0148] In variations in which a set of follow-up recommendations are generated, the follow-up recommendations can be any or all of: inserted into a predetermined section (e.g., impression section) of the radiology report; inserted into a most relevant section; not inserted into the radiology report (e.g., submitted as an addendum, inserted into a separate document, etc.); and/or otherwise utilized.
[0149] Any or all of S**300** can optionally include assessing a type of imaging (e.g., CT, MRI, LDCT, mammogram, ultrasound, etc.) associated with the scan/study and/or any other features of the study, which can function to specify what the follow-up recommendations can and/or should include (e.g., based on consensus guidelines, based on which regions of the body are able to be seen and therefore which findings would be possible to detect, etc.). This can further function to inform which follow-up recommendations to check for, to inform how to complete and/or generate follow-up recommendations, to determine which components.
[0150] In a first set of variations (e.g., as shown in FIGS. **2**A-**2**D), S**300** includes reviewing a radiology report and checking for one or more follow-up recommendations corresponding to incidental findings. In an event that the follow-up recommendations are present, the report can be flagged (e.g., with an HL7 flag) for triggering one or more actions in S**400**. In an event that the follow-up recommendations are not present, but should be based on the presence of critical incidental findings, the report can be any or all of: sent back to the radiologist for review and the addition of follow-up recommendations, annotated to include a set of follow-up recommendations determined with artificial intelligence (e.g., a set of trained models) and optionally sent back to the radiologist for review, and/or otherwise modified.
[0151] In a second set of variations, a first sub-process (e.g., with trained models) of S**300** first detects individual sentences that correspond to a recommendation (e.g., contain recommendation-like text through freeform language processing, templated language with references to consensus guidelines and/or publications, etc.), which is followed up with a second sub-process (e.g., rule-based logic) to determine one or more features associated with the set of recommendations. In specific examples, the sentences are detected based on a trained model (e.g., trained transformer model) and further processed with rule-based logic to determine what features (e.g., temporal features, type of recommendation, etc.) are associated with the recommendation. In an event that any or all of the components are missing, the recommendation can optionally be automatically completed (e.g., with a trained model, with template language and a lookup table, etc.).
[0152] In a third set of variations, any or all of a set of follow-up recommendations are automatically generated upon detecting that an incidental finding in the radiology report is not associated with a follow-up recommendation.
4.3 Method—Triggering an Action Based on the Set of Follow-Up Recommendations S**400**
[0153] The method **100** preferably includes triggering an action based on the set of follow-up recommendations S**400**, which functions to ensure that the follow-up recommendations are reliably and consistently integrated within a care plan for the patient, so that they are not overlooked, missed, or forgotten. This can subsequently function to maintain and/or improve a health of the patient (e.g., by not ignoring incidental findings, by treating incidental findings, etc.); minimizing and/or reducing the mental burden of tracking incidental findings for clinicians, radiologists, and/or healthcare facilities; increasing a number of follow-up procedures performed; and/or can perform any other suitable functions.
[0154] S**400** can further function to be customized for user preferences and/or integrated according to user (e.g., radiology group, healthcare system, radiologist, patient, PCP, etc.) requests, needs, and/or existing infrastructure. This can include, for instance, any or all of: enabling customization of the recommendation types which are tracked; enabling customization of the types of incidental

findings which are detected and/or assigned to have follow-up; integrating into existing Radiology Information System (RIS) platforms, Electronic Health Record (EHR) platforms, Picture Archiving and Communication System (PACS) platforms, and/or other software/databases associated with the user and/or customer; integrating with existing provider and/or patient portals; integrating with existing scheduling systems; and/or any can enable any other customizations and/or integrations.

[0155] The actions are preferably determined and/or selected based the incidental findings and/or the follow-up recommendations, but can additionally or alternatively be determined based on any or all of: guidelines, the patient's specific circumstances and/or condition (e.g., comorbidities), the patient's insurance and/or financial situation, other findings, patient historical information (e.g., prior imaging to show progression of finding), and/or any other information.

[0156] Examples of actions and/or outputs being triggered can include, but are not limited to, any or all of: adding follow-up recommendations to a set of worklists or other interfaces; transmitting a message or other output (e.g., text, physical mail, email, message in a healthcare platform, reminder message for user to schedule follow-up examination, etc.) to a user (e.g., patient, PCP or other physician of the patient, radiologist, other user, potential PCP, etc.), whereby transmission of messages can include automation of messaging using NLP-enhanced messaging tools. For instance, transmission of messages can include using NLP-enhanced messaging tools implementing one or more of a variety of algorithms structured to analyze, understand, and generate human language. In examples, the NLP-enhanced messaging tool can implement one or more of: Rule-based algorithms (e.g., Regular Expressions and Context-Free Grammars) structured to process text based on predefined linguistic rules; Classical machine learning techniques (e.g., Naïve Bayes algorithms, Support Vector Machines (SVM), Hidden Markov Models (HMM)) structured for tasks such as text classification, named entity recognition, and part-of-speech tagging; Deep learning models (e.g., Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Transformers (such as BERT and GPT)) structured for contextual understanding and generation of human-like text; word embedding techniques (e.g., Word2Vec, GloVe, FastText) structured to capture semantic meanings by representing words in high-dimensional vector spaces; Sequence-to-sequence (Seq2Seq) models leveraging attention mechanisms structured for tasks like machine translation and text summarization; Generative Adversarial Networks (GANs) structured for text and reinforcement learning-based approaches; and other model architecture.

[0157] Examples of actions and/or outputs can further include one or more of: flagging and/or further processing the case (e.g., study) to initiate facilitating the assignment of a PCP to a patient without a PCP (e.g., generating a referral, contacting the patient and/or PCP, establishing communication between the patient and a PCP, etc.); automatically generating a imaging order (e.g., through a RIS, with a fax, with a message, with a scheduling tool, etc.) for initiation and/or confirmation (e.g., by the patient, by the PCP, etc.); providing customizable interfaces (e.g., worklists) and/or analytics to a manager (e.g., nurse navigator, facilitator, radiology assistant, radiology department manager, head of a radiology group, etc.) or other user; and/or any other actions/outputs can be triggered.

[0158] S**400** is preferably performed in response to S**300**, but can additionally or alternatively be performed in response to another process of the method (e.g., S**200**), prior to any processes of the method, multiple times (e.g., at a predetermined frequency, at a random set of intervals, etc.), and/or at any other suitable time(s).

[0159] S**400** is preferably performed at least partially automatically, wherein any or all of the triggers are automatically set and implemented (e.g., according to a schedule, based on a detected trigger, etc.). Additionally or alternatively, S**400** can be performed manually, and/or any combination of manually and automatically.

[0160] S**400** can optionally include communicating the set of incidental findings and/or the associated follow-up recommendations, which can function to ensure that an appropriate entity is notified of this information. Communicating the set of findings can optionally include generating (e.g., auto-generating) and/or transmitting (e.g., auto-transmitting) one or more notifications (e.g., messages, alerts, etc.), wherein the notifications can be transmitted to any or all of: a physician/clinician (e.g., emergency room physician, patient's primary care physician, specialist physician, etc.), a healthcare facility and/or associated database (e.g., to be included in patient's medical record); the patient (e.g., to make them aware of follow-up they should initiate); a computing system (e.g., for further processing, for tracking, etc.); and/or any other individuals and/or entities.

[0161] In some variations, for instance, S**400** includes automatically notifying (e.g., through a text message, email, call, mail, etc.) the patient of his or her incidental findings and the associated follow-up recommendations. Additionally or alternatively, S**400** can include automatically notifying the patient's primary care physician and/or any other outpatient providers of the incidental findings and/or follow-up, such that the physician can be made aware and take any measures that he or she sees fit for the patient.

[0162] S**400** can optionally additionally or alternatively include establishing communication between multiple entities. This can include communication between the patient and a physician (e.g., primary care physician) such that the physician can provide guidance on follow-up steps; between multiple physicians (e.g., between an attending physician and an outpatient physician, between an ER physician and an outpatient provider, etc.); between a radiologist and a physician (e.g., between the radiologist filling out the report and the patient's primary care physician, between the radiologist filling out the report and an attending physician at the same healthcare facility for immediate treatment, etc.); between systems and/or databases (e.g., through an HL7 message); and/or between any other entities. Establishing communication can include any or all of: providing contact information; setting up a message thread; sending notifications; initiating a phone call and/or conference call; sending a fax (e.g., faxed discharge summary, faxed discharge order, etc.); and/or any other communication can be suitably established.

[0163] In a first variation, S**400** includes communicating the incidental findings and the follow-up recommendations to a physician responsible for the patient after discharge from the healthcare facility performing the imaging. This can include a message, call, alert, update to the patient's medical file, and/or any other suitable communication.

[0164] In a second variation, S**400** includes communicating the follow-up recommendations directly to the patient.

[0165] In a third variation (e.g., as shown in FIG. **7**A), S**400** includes facilitating the assignment of a PCP to a patient upon determining that the patient does not currently have a PCP. This can include, for instance, any or all of: compiling (e.g., automatically compiling) and sending a list of PCP options (e.g., based on their availability, based on their proximity to the patient, based on the patient's insurance, etc.) to the patient; contacting the recommended PCP(s) and notifying them of the patient; referring the patient to the PCP; and/or triggering any other actions.

[0166] S**400** can optionally include scheduling any or all of the follow-up recommendations, such as automatically scheduling any or all of: follow-up imaging; one or more appointments (e.g., with a primary care physician, with a specialist, etc.) and/or specialist consultations; laboratory testing; a procedure; emergency intervention; and/or any other suitable follow-up. Scheduling the follow-up can optionally include interfacing with one or more systems and/or interfaces, such as any or all of: a healthcare facility scheduling system; the calendar and/or availability of the patient; the calendar and/or availability of a physician; the calendar and/or availability of a radiologist and/or laboratory technician; and/or any other systems.

[0167] At least a portion of the actions and/or outputs are preferably performed and/or triggered automatically (e.g., without user input), but any or all can additionally or alternatively be partially or fully performed manually (e.g., by a user).

[0168] In some variations, for instance, S**400** can include automatically scheduling follow-up imaging at a predetermined later time point according to the follow-up recommendation.

[0169] S**400** can optionally include organizing any or all patients and/or reports, which can function to enable one or more users to view, manage, and/or prioritize any or all of the actions and/or outputs associated with a follow-up recommendation. The user preferably includes one or more users involved in a case and/or patient management capacity, such as, but not limited to: a case manager (e.g., for a radiology department, radiology group, healthcare facility, department, etc.), facilitator, nurse navigator, and/or any other managers associated with a healthcare facility, radiology group, and/or any other entities. Additionally or alternatively, the information can be accessible by (e.g., continuously accessible by, selectively accessibly by, accessible by in an event of a particular action/trigger, etc.): patients, radiologists, physicians (e.g., PCPs), all users, others users, and/or any combination of users.
[0170] In a preferred set of variations, for instance, S**400** includes automatically populating, managing, and organizing a set of one or more worklists accessible by one or more users for tracking and managing the actions and/or outputs for patient follow-up. In a set of specific examples (e.g., as shown in FIGS. **7**A-**7**E), a follow-up worklist is created and populated which enables users to view, track, and manage the actions and outputs specified by the follow-up recommendations determined in S**300**.
[0171] The worklists (and/or any other interfaces) can optionally receive information regarding events that happen outside of this system and/or facility (e.g., from RIS, EHR, etc.) in order to automatically update the status (e.g., if imaging happens) of follow-up actions. Additionally or alternatively, historical information associated with the patient (e.g., findings and/or follow-up recommendations from prior studies) can be received and used in determining and/or managing the outputs and/or actions.
[0172] The follow-up worklist can optionally be split and/or configured to be viewed into multiple worklists. In some variations (e.g., as shown in FIG. **6**), for instance, in an event that a follow-up recommendation is incomplete and/or missing, the patient and associated radiology report can be populated within a secondary worklist, which can function to alert the manager or other user that a follow-up recommendation is missing (e.g., to trigger the report being sent back to the radiologist for completion, for completion by the manager or other user, for validation by the manager or other user of an auto-generated recommendation, etc.), whereas complete radiology reports populate a primary worklist.
[0173] The worklists and/or other interfaces can optionally be sorted and/or filtered (e.g., as shown in FIGS. **7**A-**7**E), which can function to: help users prioritize which patients to follow up with (e.g., manually); trigger supplemental actions and/or outputs (e.g., in response to the patient not performing an action within a predetermined threshold of time); determine (e.g., quickly determine) how overdue an action might be; ensure that the follow-up recommendations are performed and/or complied with; prevent patients from being forgotten and/or ignored; and/or can perform any other functions. In a first set of examples, the patients in one or more worklists are sorted according to one or more temporal parameters (e.g., due date, number of days a follow-up action is overdue, etc.) associated with their follow-up recommendations. Additionally or alternatively, any or all of the temporal parameters can be used to determine a progress metric (e.g., according to a predetermined equation, aggregated in a weighted fashion, etc.) associated with the patient's progress in completing his or her triggered actions. Further additionally or alternatively, the progress metric can take into account any or all of: a number of actions/outputs which have been completed; an average time in which the actions/outputs are completed; a number of days in which an action/output has been completed or not completed relative to a predetermined time limit associated with the action; and/or any other information. In a second set of examples, the patients are additionally or alternatively sorted according to the particular finding detected in their study, such as based on a severity metric and/or urgency metric associated with the particular finding (e.g., as determined with a lookup table, as determined with a weighted algorithm, etc.). In a third set of specific examples, the patients are additionally or alternatively sorted based on demographic

and/or historical information associated with the patient, such as: other comorbidities associated with the patient, a risk metric determined based on demographic information and/or historical health information of the patient, a progression of the finding (e.g., based on prior studies); and/or any other information. In a particular specific example, a risk metric is calculated based on any or all of this information, where the patients are sorted to indicate the highest risk patients first.

[0174] S**400** can optionally include tracking any or all of the follow-up recommendations, which can function to ensure that follow-up is performed, monitor incidental findings which do not have current specific follow-up, determine when follow-up no longer needs to be continued (e.g., in an event that the incidental finding is improving and/or no longer present), and/or can perform any other functions.

[0175] The tracking can include, for instance, automatically sending notifications to any or all of the entities described above, such as at a predetermined frequency (e.g., every month, every 3 months, every 6 months, every year, etc.) until the follow-up is performed. Additionally or alternatively, tracking can include routinely checking the patient's medical information (e.g., medical files, PACS, etc.) to see if the follow-up has been performed.

[0176] In a set of specific examples, the tracking includes tracking the same incidental finding and/or or group of incidental findings in the same body system across multiple follow-up studies and/or other actions for any predetermined and/or dynamically determined time period (e.g., over the course of multiple years, until a predetermined number of years has passed, etc.)

[0177] S**400** can additionally or alternatively include any or all of: checking to see if follow-up is performed; verifying that the follow-up is performed; and verifying that the follow-up which was performed satisfies the associated recommendation. These can individually and/or collectively function to effectively “close the loop” on the patient and/or study and/or set of follow-up recommendations (e.g., to trigger removal of the patient from a set of worklists, to cease sending messages and/or reminders to one or more users, etc.). In preferred variations, these processes are performed at least partially automatically (e.g., all fully automatically), but can additionally or alternatively be performed at least partially manually (e.g., with user input), and/or any combination of automatically and manually.

[0178] In a first set of variations, for instance, S**400** includes detecting whether or not an action performed by or for the patient satisfies the follow-up recommendation and/or a set of requirements associated with the set of follow-up recommendations. These can include any or all of: actions which are associated with (e.g., triggered based on) a particular finding and/or follow-up recommendation (e.g., an imaging study automatically scheduled in response to a particular follow-up recommendation; actions which are performed independently of a finding and/or follow-up recommendation (e.g., routinely performed, ordered for another reason, etc.); any combination; and/or any other actions.

[0179] In some examples, for instance, whenever additional studies are done for the patient (e.g., even if not ordered specifically to follow up that incidental finding), S**400** can include detecting (e.g., automatically detecting) whether or not the study satisfies any or all requirements associated with follow-up for the patient (e.g., pending/outstanding follow-up requirements) and optionally closing out the follow-up recommendation in response to satisfaction of any or all criteria. This preferably applies to all studies or other actions associated with the patient, such as, but not limited to: studies performed at other healthcare facilities (e.g., facilities outside of the patient's catchment area), studies performed for other reasons, and/or any other studies. Examples of these requirements can include, but are not limited to, any or all of: detecting that the study imaged a required area; detecting that the same incidental finding was mentioned again in that study's associated report; detecting that the study falls within a recommended timeframe (e.g., with a customizable grace period, without a customizable grace period, etc.); and/or detecting any other information/features associated with the performed action. Additionally or alternatively, S**400** can include closing the loop (e.g., cancelling further follow-up actions, removing from a worklist, etc.)

on a patient upon determining and/or receiving an input (e.g., from the patient's provider) that indicates that any or all follow-up actions (e.g., further study) is not clinically necessary and/or recommended (e.g., due to the patient's existing comorbidities, due to the patient's advanced age, etc.).

[0180] Additionally or alternatively, S**400** can include any other suitable processes, such as automatically creating one or flags (e.g., in the radiology report, in notes for a physician, in a discharge order, etc.), and/or any other suitable processes.

4.4 Method-Variations

[0181] In a first variation of the method S**200** (e.g., as shown in FIG. **4**), the method S**200** includes any or all of: processing a radiology report to locate a findings section and/or set of findings; evaluating (e.g., with a set of trained models and/or algorithms, with natural language processing, with a set of lookup tables, with a decision tree, with a set of trained classifiers, etc.) the located findings to classify any or all of the set of findings; identifying a set of incidental findings based on the classification(s); locating a set of follow-up recommendations in the radiology report; associating each of the set of incidental findings with one or more follow-up recommendations; in an event that any of the follow-up recommendations for an incidental finding are incomplete and/or missing, triggering an action (e.g., auto-completing the recommendation, automatically generating the recommendation, flagging/providing the report to a user for completion, etc.); determining a set of actions and/or outputs configured to facilitate and ensure performance of the follow-up recommendations; and triggering the set of outputs and/or actions.

[0182] In a first set of specific examples, the method S**200** includes any or all of: processing the radiology report with a set of trained models (e.g., trained machine learning models, trained deep learning models, trained neural networks, natural language processing models, etc.) to determine/detect any or all of: a findings section and/or a set of findings in the radiology report (e.g., based on a predetermined set of keywords associated with particular findings and/or findings collectively); a set of follow-up recommendations; an association between any or all of the set of findings and any or all of the set of recommendations (e.g., associating each of the set of incidental findings with its corresponding follow-up recommendation(s)); a missing and/or incomplete follow-up recommendation; an optimal output and/or action to trigger (e.g., as determined with a predictive model); an optimal time and/or recipient at/to which trigger the output and/or action; and/or any other determinations or detections.

[0183] In a second set of examples, additional or alternative to the first, checking for the set of findings is performed prior to checking for and/or determining the set of follow-up recommendations.

[0184] In a third set of examples, additional or alternative to those described above, checking for the set of findings is performed after checking for and/or locating the set of follow-up recommendations.

[0185] In a fourth set of examples, additional or alternative to those described above, checking for the set of findings is performed in parallel with checking for and/or locating and/or generating the set of follow-up recommendations.

[0186] In a fifth set of examples, additional or alternative to those described above, the method S**200** is performed in absence of one or both of: checking for the set of findings and checking for (and/or locating and/or generating) the set of follow-up recommendations.

[0187] In a second variation of the method S**200** (e.g., as shown in FIG. **4**), the method S**200** includes: processing a set of images with a set of models and/or algorithms (e.g., trained models) to automatically detect a set of incidental findings associated with the images (and optionally any other findings); determining (e.g., automatically generating) a set of follow-up recommendations (e.g., with a set of models and/or algorithms) associated with any or all of set of findings; inserting the follow-up recommendations into a radiology report (e.g., new radiology report, existing radiology report which is partially finished, etc.); determining a set of actions and/or outputs configured to facilitate and ensure performance of the follow-up recommendations; and triggering the set of outputs and/or actions. The method S**200** can optionally additionally or alternatively include any or all of: receiving a radiology report (e.g., manually generated radiology report, automatically generated radiology report, partially finished radiology report, etc.); locating an existing set of findings within the radiology report; and comparing the set of findings (e.g., incidental findings) in the radiology report with those automatically generated (e.g., to detect if any incidental findings are missing in the report).

[0188] In a third variation of the method S**200** (e.g., as shown in FIG. **4**), the method S**200** includes: processing a radiology report to locate a set of follow-up recommendations in the radiology report; processing the set of follow-up recommendations to detect a completion associated with each of the set of follow-up recommendations; and in response to detecting that any or all of the follow-up recommendations are incomplete, performing at least one of assigning the report and/or associated study and/or patient to a secondary dataset (e.g., secondary worklist) and automatically generating and inserting a missing portion of the follow-up recommendation into the radiology report.

[0189] In a first set of examples, the method S**200** includes referencing a predetermined lookup table to generate and/or complete the set of follow-up recommendations. The predetermined lookup table preferably includes, is generated based on, and/or is generated in accordance with a set of radiology consensus guidelines, radiology best practices, a set of preferences (e.g., of the radiology group, of the patient, of the patient's primary care physician, etc.), and/or any other information.

[0190] In a second set of examples, the method S**200** generates and/or completes a set of follow-up recommendations with a set of models and/or algorithms (e.g., trained machine learning models, neural networks, etc.).

[0191] In a third set of examples, additional or alternative to those described above, in response to detecting that a follow-up recommendation is missing and/or incomplete, the method S**200** automatically triggers an assignment of the study to a secondary worklist associated with a user, such that the user can complete and/or flag the study for completion (e.g., by the radiologist who generated the report).

[0192] According to an additional variation, where the additional variation can be performed in coordination with or separate from method steps described above, as shown in FIGS. **16**A and **16**B, a method **500** can include: providing an interface S**510** for single-input approval of a clinical follow-up recommendation generated automatically using a trained multi-transformer model, upon: receiving a radiology report S**520** associated with a set of radiology images from a patient of an institution, from a Picture Archiving and Communication System (PACS); processing the radiology report S**530** with the trained multi-transformer model to determine a set of classifications, the method further comprising generating the trained multi-transformer model upon training S**535**, with a computing subsystem remote from the PACS, a multi-transformer model with training data from reports from a set of institutions and involving a set of actionable findings; at the interface, returning: a) a finding summary for the radiology report, from the trained multi-transformer model, b) a set of follow-up recommendations comprising a promoted follow-up recommendation from the trained multi-transformer model, and c) an input-receiving object for approving execution of the promoted follow-up recommendation S**540**; upon receiving a single-input to the input-receiving object from a user of the interface, executing the promoted follow-up recommendation S**550** by providing computer-readable instructions for a Radiology Information System (RIS); and confirming completion of the promoted follow-up recommendation S**560** for a patient upon interrogating the Radiology Information System (RIS). Embodiments, variations, and examples of the steps of method **500** can be performed by the computing system and/or processing system elements described above, where such systems include architecture for performing method steps and controlling, with computer-readable control instructions, other systems that can be implemented to automatically execute and confirm completion of follow-up recommendations.

[0193] Aspects of the multi-transformer model of the method **500** can include LLM and/or non-LLM architecture, as described above. In examples, LLM architecture can include a version of the Pathways Language Model (e.g., PaLM, PaLM2, etc.). Variations of the LLM can include a version of a Language Model for Dialogue Applications (LaMDA), a Gemini model (e.g., a decoder-only transformer), a GPT model, a Llama model, a GLM model, a Claude model, a Reka Flash model, a Qwen model, a Grok model, a Molmo model, a Jamba model, a DeepSeek Coder model, an Athene model, a Phi-3 model, a Command-R-Plus model, an InternLM model, a Yi-Large model, a Mixtral of Experts model, a Gemma model, a Nemotron model, and/or another suitable model.

[0194] Providing the interface in Block S**510** can include providing an embodiment, variation, or example of the interface **235** described in relation to system **200** above, where, in variations, the interface provides a mechanism for executing follow-up recommended actions responsive to findings extracted from radiology reports by artificial intelligence (AI) models, upon acceptance of a single input from a user of the interface. Furthermore, in specific examples, any or all of the method can performed in absence of input from a radiologist or other user, which can be equivalently referred to herein as a “zero-click” process.

[0195] In relation to the interface, as shown in FIG. **16**B, the method can further include Step S**515**, which recites: presenting an organized set of finding summaries paired with a set of promoted follow-up recommendations generated upon processing a backlog of radiology reports with the trained multi-transformer model, for the institution, at an initial interaction with the interface. Step S**515** functions to pre-process a historical backlog of radiology reports, such that new users of the method **500** and/or interfaces described are immediately presented with tools for efficiently processing the historical backlog. In examples, the systems and methods described can pre-process up to 6 months of a historical backlog of radiology reports, up to 1 year of a historical backlog of radiology reports, up to two years of a historical backlog of radiology reports, up to 3 years of a historical backlog of radiology reports, up to 4 years of a historical backlog of radiology reports, up to 5 years of a historical backlog of radiology reports, up to 6 years of a historical backlog of radiology reports, up to 7 years of a historical backlog of radiology reports, up to 8 years of a historical backlog of radiology reports, up to 9 years of a historical backlog of radiology reports, up to 10 years of a historical backlog of radiology reports, or greater. Pre-processing can include generating, for each report in the historical backlog, a finding summary and a set of follow-up recommendations (including a promoted follow-up recommendation that can be executed with a single-input approval action). Processing the historical backlog of radiology reports can further include one or more of: providing a historical benchmark of performance for processing radiology reports (e.g., at the institution); using historical backlog to train the model(s) described for automatically extracting findings and returning finding summaries and promoted follow-up recommendations for approval and execution.

[0196] As such, in variations of Step S**515**, during an initial interaction with the interface, a user can be presented with a backlog of finding summaries generated from historical radiology reports, along with corresponding promoted recommended follow-up actions. As such, methods described can include presenting an organized set of finding summaries paired with a set of promoted follow-up recommendations generated upon processing a backlog of radiology reports with the trained multi-transformer model, for an institution, at an initial interaction with the interface. In examples, the methods and systems described can reduce the historical backlog of open radiology reports by at least 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90%, or greater, within 7 days, within 6 days within 5 days, within 4 days, within 3 days, within 2 days, within 1 day, within 22 hours, within 20 hours, within 18 hours, within 16 hours, within 14 hours, within 12 hours, within 10 hours, within 8 hours, within 6 hours, within 4 hours, or less, upon receiving a set of single-inputs for executing a subset of the set of promoted follow-up recommendations, at the interface.

[0197] In relation to Steps S**510**-S**540**, a finding summary of extracted findings can include finding categorizations and finding subcategorizations, where categorizations and subcategorizations are described in relation to classifications and other features described below.

[0198] In relation to Steps S**550** and S**560**, executing follow-up recommendations and confirming completion of follow-up recommendations can be automatically performed using computing system and/or processing system aspects described above. As such, Steps S**550** and S**560** can include performing steps for confirming completion of a recommended follow-up (e.g., promoted recommended follow-up, where the promoted recommended follow-up is the most appropriate or highest-ranked follow-up action in a list of recommended follow-up candidates), In one example, confirming completion of the follow-up recommendation can include receiving a notification, at an embodiment of the interface described, that the promoted follow-up recommendation was completed, upon interrogating the patient using a natural language processing (NLP)-enhanced messaging tool by the system, and transmitting the notification to be rendered at the interface. Completion of the promoted follow-up recommendation can be performed at the institution where the user interacts with the interface, or alternatively, at a second institution different than the institution. As such, tracking of follow-up completion can be performed automatically, using the NLP-enhanced messaging tool, regardless of which institution cares for a patient. NLP-enhanced messaging tools associated with the systems and interfaces described can implement one or more of a variety of algorithms structured to analyze, understand, and generate human language. In examples, the NLP-enhanced messaging tool can implement one or more of: Rule-based algorithms (e.g., Regular Expressions and Context-Free Grammars) structured to process text based on predefined linguistic rules; Classical machine learning techniques (e.g., Naïve Bayes algorithms, Support Vector Machines (SVM), Hidden Markov Models (HMM)) structured for tasks such as text classification, named entity recognition, and part-of-speech tagging; Deep learning models (e.g., Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Transformers (such as BERT and GPT)) structured for contextual understanding and generation of human-like text; word embedding techniques (e.g., Word2Vec, GloVe, FastText) structured to capture semantic meanings by representing words in high-dimensional vector spaces; Sequence-to-sequence (Seq2Seq) models leveraging attention mechanisms structured for tasks like machine translation and text summarization; Generative Adversarial Networks (GANs) structured for text and reinforcement learning-based approaches; and other model architecture.

[0199] Embodiments of the system and/or method can include every combination and permutation of the various system components and the various method processes, wherein one or more instances of the method and/or processes described herein can be performed asynchronously (e.g., sequentially), contemporaneously (e.g., concurrently, in parallel, etc.), or in any other suitable order by and/or using one or more instances of the systems, elements, and/or entities described herein. Components and/or processes of the following system and/or method can be used with, in addition to, in lieu of, or otherwise integrated with all or a portion of the systems and/or methods disclosed in the applications mentioned above, each of which are incorporated in their entirety by this reference.

[0200] Additional or alternative embodiments implement the above methods and/or processing modules in non-public transitory computer-readable media, storing computer-readable instructions. The instructions can be executed by computer-executable components integrated with the computer-readable medium and/or processing system. The computer-readable medium may include any suitable computer readable media such as RAMs, ROMs, flash memory, EEPROMs, optical devices (CD or DVD), hard drives, floppy drives, non-public transitory computer readable media, or any suitable device. The computer-executable component can include a computing system and/or processing system (e.g., including one or more collocated or distributed, remote or local processors) connected to the non-public transitory computer-readable medium, such as CPUs, GPUs, TPUS, microprocessors, or ASICs, but the instructions can alternatively or additionally be executed by any suitable dedicated hardware device.

[0201] As a person skilled in the art will recognize from the previous detailed description and from the figures and claims, modifications and changes can be made to the preferred embodiments of the invention without departing from the scope of this invention defined in the following claims.

Claims

1. A method comprising: providing an interface for single-input approval of a clinical follow-up recommendation generated automatically using a trained multi-transformer model, upon: receiving a radiology report associated with a set of radiology images from a patient of an institution, from a Picture Archiving and Communication System (PACS); processing the radiology report with the trained multi-transformer model to determine a set of classifications, the method further comprising generating the trained multi-transformer model upon training, with a computing subsystem remote from the PACS, a multi-transformer model with training data from reports from a set of institutions and involving a set of actionable findings; at the interface, returning: a) a finding summary for the radiology report, from the trained multi-transformer model, b) a set of follow-up recommendations comprising a promoted follow-up recommendation from the trained multi-transformer model, and c) an input-receiving object for approving execution of the promoted follow-up recommendation; upon receiving a single-input to the input-receiving object from a user of the interface, executing the promoted follow-up recommendation by providing computer-readable instructions for a Radiology Information System (RIS); and confirming completion of the promoted follow-up recommendation for a patient upon interrogating the Radiology Information System (RIS).
2. The method of claim 1, wherein the trained multi-transformer model comprises a large language model.
3. The method of claim 1, wherein the trained multi-transformer model comprises a non-large-language model.
4. The method of claim 1, wherein the trained multi-transformer model comprises a set of decoders, each of the set of decoders structured to consult multiple encoders in parallel.
5. The method of claim 1, wherein the trained multi-transformer model implements parallelization architecture that does not require processing of data in any order.
6. The method of claim 1, wherein the interface reduces a number of full-time equivalent (FTE) users required to initiate execution of follow-up recommendations for a set of radiology reports by 75%.
7. The method of claim 1, wherein executing the promoted follow-up recommendation and confirming completion of the promoted follow-up recommendation comprises controlling information flow through the RIS.
8. The method of claim 1, wherein confirming completion of the promoted follow-up recommendation comprises receiving a notification, at the interface, that the promoted follow-up recommendation was completed at a second institution different from the institution, upon interrogating the patient using a natural language processing (NLP)-enhanced messaging tool, and transmitting the notification to be rendered at the interface.
9. The method of claim 1, wherein the set of actionable findings comprises a finding associated with a Lung-RADS category, a cardiac condition, or a BI-RADS category.
10. The method of claim 1, further comprising: presenting an organized set of finding summaries paired with a set of promoted follow-up recommendations generated upon processing a backlog of radiology reports with the trained multi-transformer model, for the institution, at an initial interaction with the interface.
11. The method of claim 10, further comprising reducing the backlog by at least 50% within 4 days, upon receiving a set of single-inputs for executing a subset of the set of promoted follow-up recommendations, at the interface.
12. The method of claim 1, wherein executing the promoted follow-up recommendation comprises automatically generating an imaging order through the Radiology Information System (RIS).

13. The method of claim 1, further comprising: at the computing system, determining that at least one of the set of classifications indicates a missed incidental finding that was missed by a radiologist generating the radiology report, the method further comprising through at least one of the RIS and the interface, returning the radiology report to a queue of the radiologist in response to the missed incidental finding.
14. The method of claim 1, wherein the promoted follow-up recommendation comprises at least one of: a scan, a bloodwork order, and a specialist appointment.
15. The method of claim 1, wherein the finding summary comprises a categorization and a subcategorization of a finding of the radiology report.
16. The method of claim 1, wherein the set of classifications comprises at least one of a Lung-RADS category or a BI-RADS category.
17. A system comprising an interface configured for single-input approval of a clinical follow-up recommendation; and a processing system in communication with the interface, a Picture Archiving and Communication System (PACS), and a Radiology Information System (RIS) and comprising a trained multi-transformer model, wherein the computing system comprises instructions stored in a non-transitory medium that, when executed, perform; generating the trained multi-transformer model upon training, with a computing subsystem remote from the PACS, a multi-transformer model with training data from reports from a set of institutions and involving a set of actionable findings; receiving a radiology report associated with a set of radiology images from a patient of an institution, from the PACS; processing the radiology report with the trained multi-transformer model to determine a set of classifications; causing to render, at the interface: a) a finding summary for the radiology report, from the trained multi-transformer model, b) a set of follow-up recommendations comprising a promoted follow-up recommendation from the trained multi-transformer model, and c) an input-receiving object for approving execution of the promoted follow-up recommendation; upon receiving a single-input to the input-receiving object from a user of the interface, executing the promoted follow-up recommendation by providing computer-readable instructions for a Radiology Information System (RIS); and confirming completion of the promoted follow-up recommendation for a patient upon interrogating the RIS.
18. The system of claim 17, wherein the trained multi-transformer model comprises a large language model.
19. The system of claim 17 wherein the trained multi-transformer model implements parallelization architecture that does not require processing of data in any order.
20. The system of claim 17, wherein the interface is structured to reduce a number of full-time equivalent (FTE) users required to initiate execution of follow-up recommendations for a set of radiology reports by 75%.