



US012387109B1

(12) **United States Patent**
Giannulli et al.

(10) **Patent No.:** **US 12,387,109 B1**
(45) **Date of Patent:** ***Aug. 12, 2025**

(54) **SYSTEMS AND METHODS FOR
AUTOMATED SCRIBES BASED ON
KNOWLEDGE GRAPHS OF CLINICAL
INFORMATION HAVING WEIGHTED
CONNECTIONS**

(71) Applicant: **AMERICAN MEDICAL
ASSOCIATION**, Chicago, IL (US)

(72) Inventors: **Thomas Giannulli**, Newport Beach,
CA (US); **Joshua Samuel Schwartz**,
Laguna Niguel, CA (US)

(73) Assignee: **American Medical Association**,
Chicago, IL (US)

(*) Notice: Subject to any disclaimer, the term of this
patent is extended or adjusted under 35
U.S.C. 154(b) by 852 days.

This patent is subject to a terminal dis-
claimer.

(21) Appl. No.: **17/671,399**

(22) Filed: **Feb. 14, 2022**

Related U.S. Application Data

(60) Provisional application No. 63/150,993, filed on Feb.
18, 2021.

(51) **Int. Cl.**
G06N 5/02 (2023.01)
G06F 18/20 (2023.01)
(Continued)

(52) **U.S. Cl.**
CPC **G06N 5/02** (2013.01); **G06F 18/29**
(2023.01); **G06N 5/022** (2013.01); **G06N**
20/00 (2019.01);
(Continued)

(58) **Field of Classification Search**
CPC G06N 5/02; G06N 5/022; G06N 20/00;
G06F 18/29; G16H 10/60; G16H 50/70;
G16H 70/20
See application file for complete search history.

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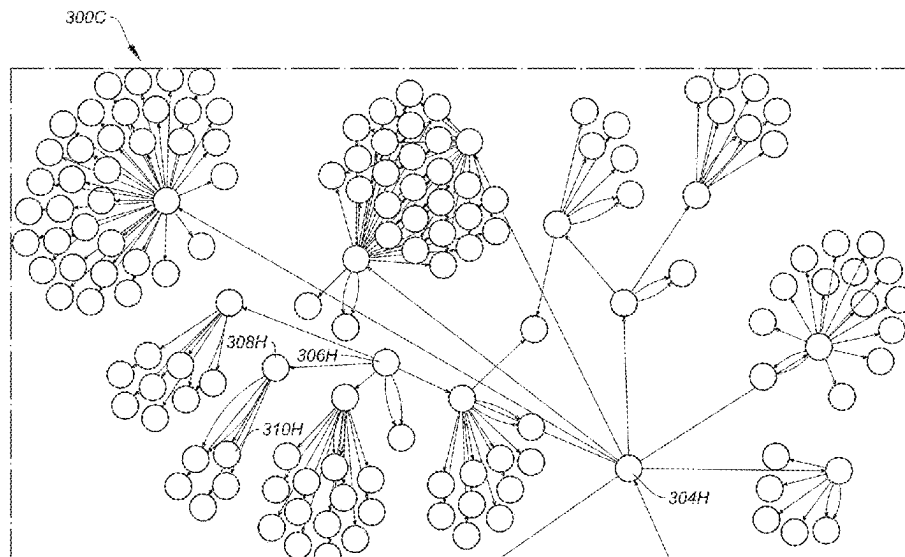
Primary Examiner — James T Tsai

(74) *Attorney, Agent, or Firm* — Faegre Drinker Biddle &
Reath LLP

(57) **ABSTRACT**

Method, system, device, and non-transitory computer-read-
able medium for generating a knowledge graph of clinical
information. In some examples, a computer-implemented
method includes: identifying a clinical encounter associated
with a clinical concern; representing the clinical concern as
a module of a knowledge graph of clinical information;
associating at least one section node with the module, each
section node of the at least one section node corresponding
to a clinical concept relevant to the clinical concern; asso-
ciating, for each section node of the at least one section
node, at least one topic node with the section node, each
topic node of the at least one topic node corresponding to a
clinical topic relevant to the corresponding clinical concept;
and generating the knowledge graph of clinical information
to represent the clinical concern, the relevant clinical con-
cepts, and the relevant clinical topics.

28 Claims, 10 Drawing Sheets



- (51) **Int. Cl.**
G06N 5/022 (2023.01)
G06N 20/00 (2019.01)
G16H 10/60 (2018.01)
G16H 50/70 (2018.01)
G16H 70/20 (2018.01)
- (52) **U.S. Cl.**
CPC **G16H 10/60** (2018.01); **G16H 50/70**
(2018.01); **G16H 70/20** (2018.01)

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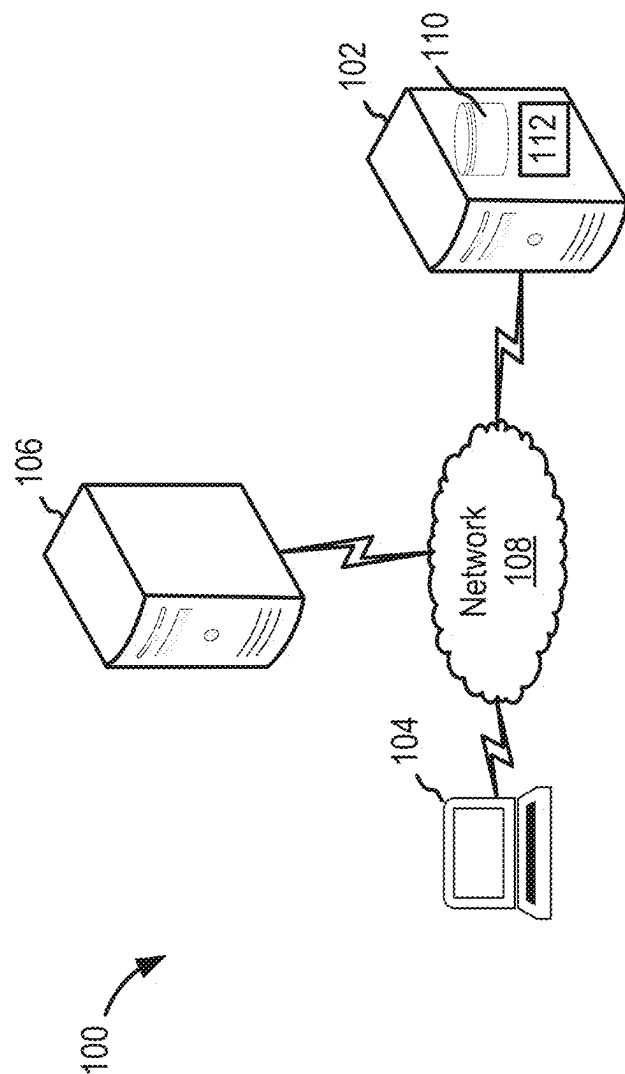
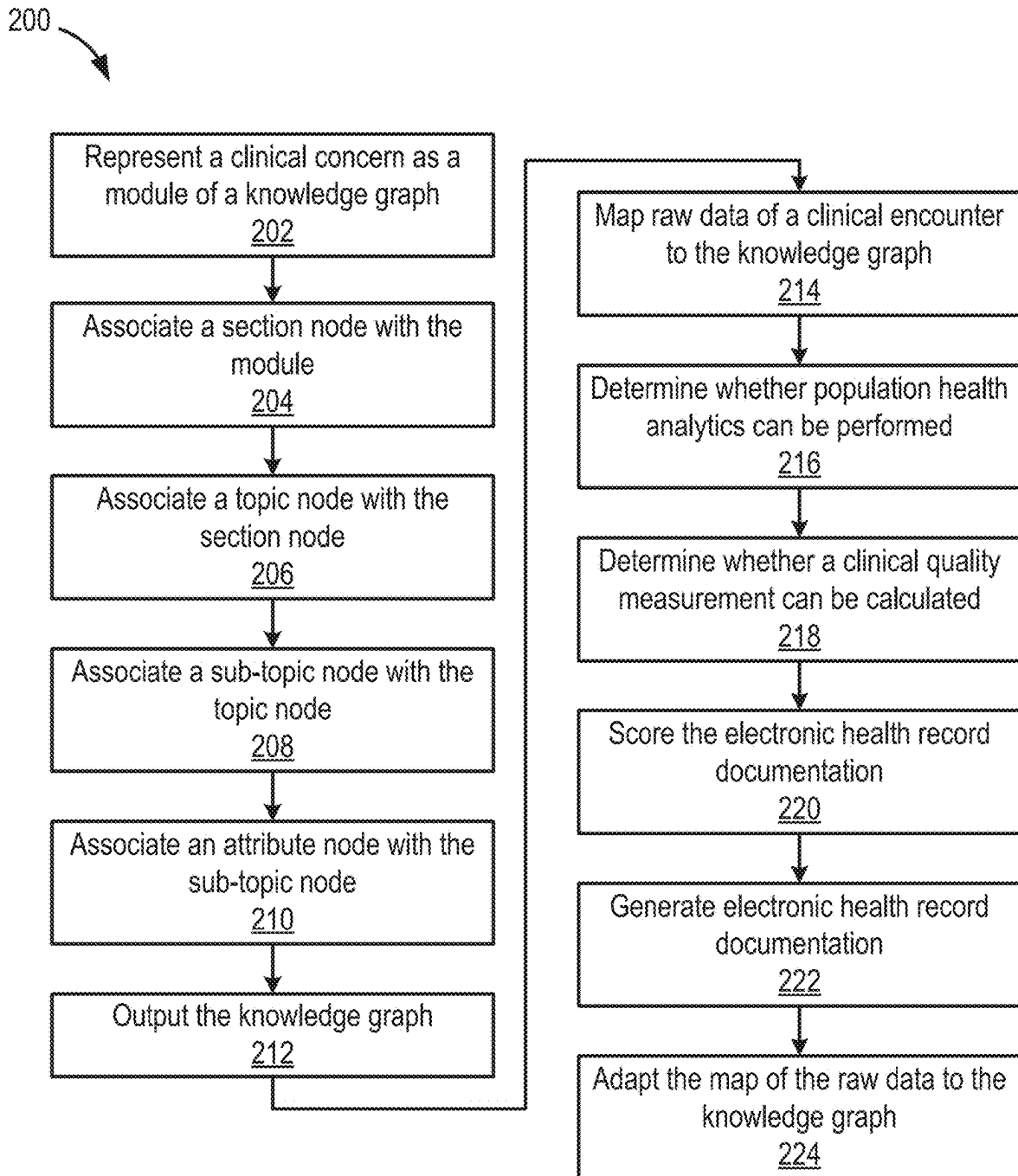
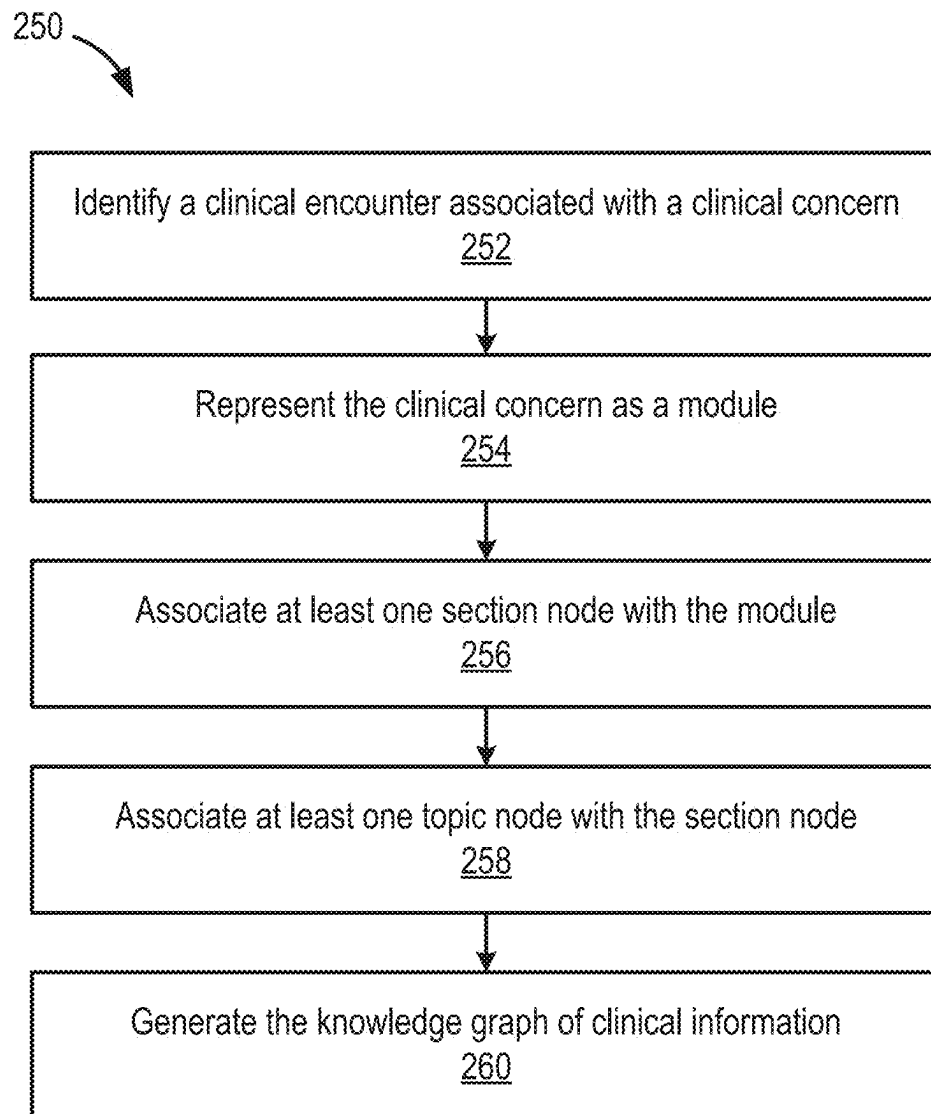


Fig. 1

**Fig. 2A**

**Fig. 2B**

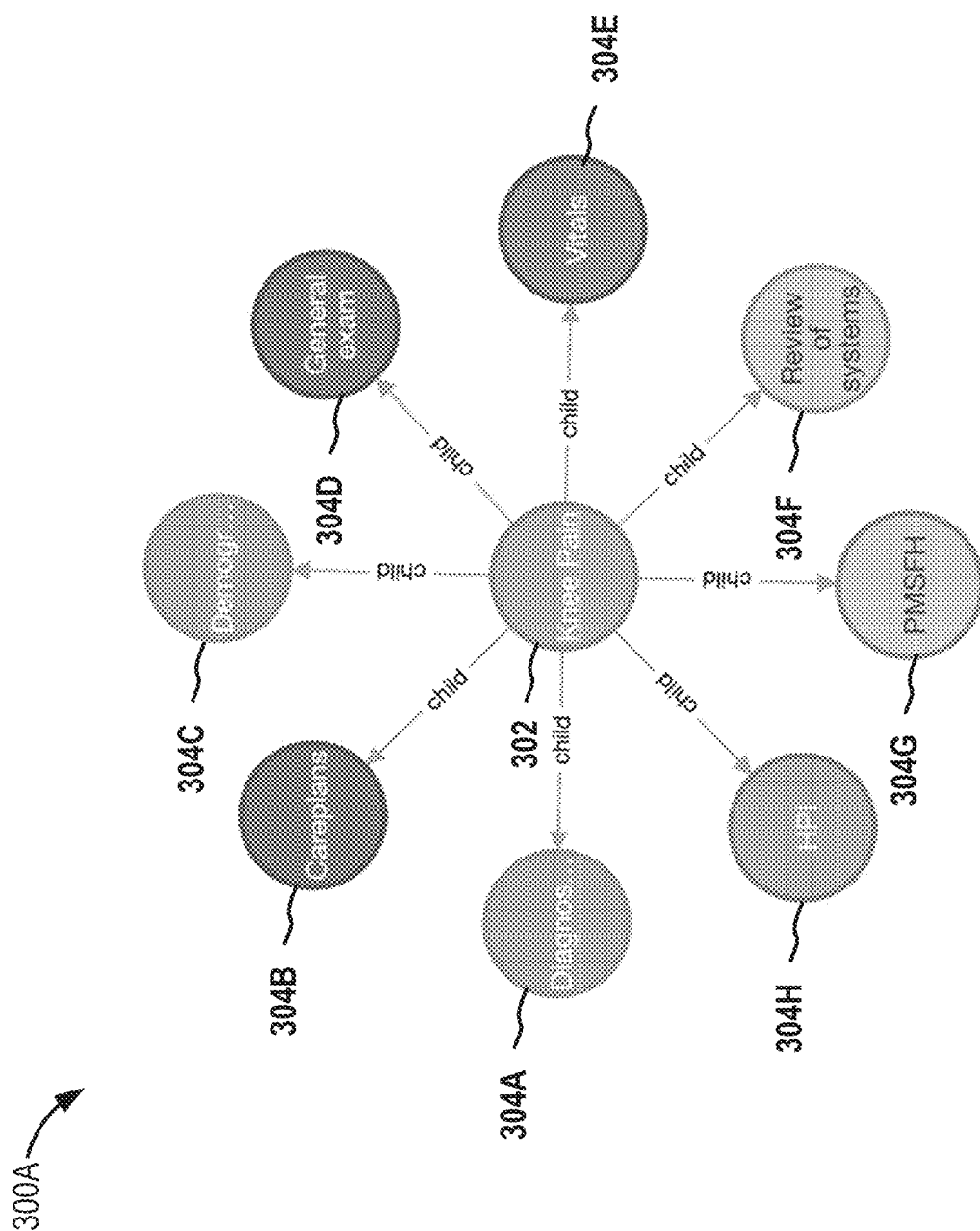
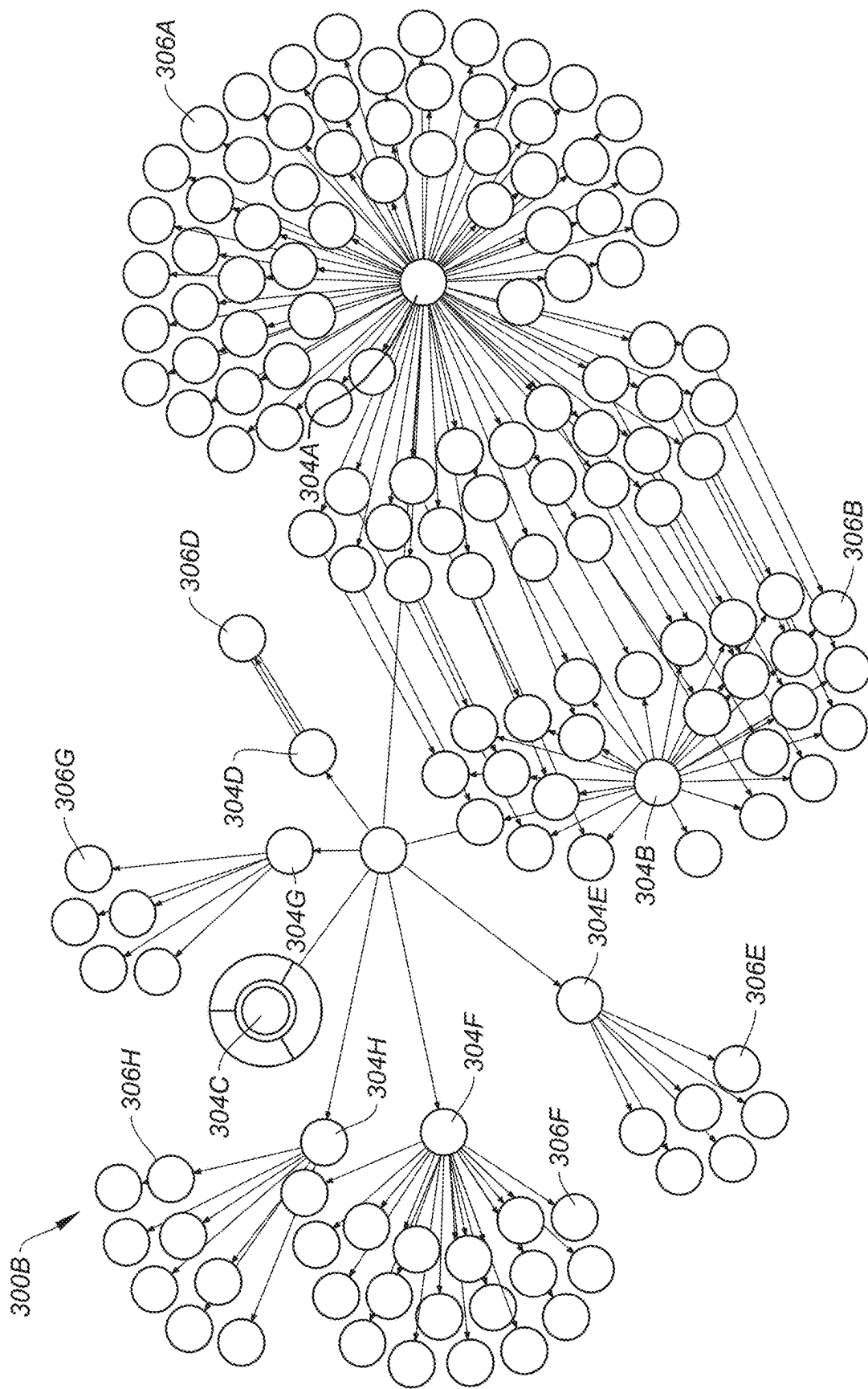


Fig. 3



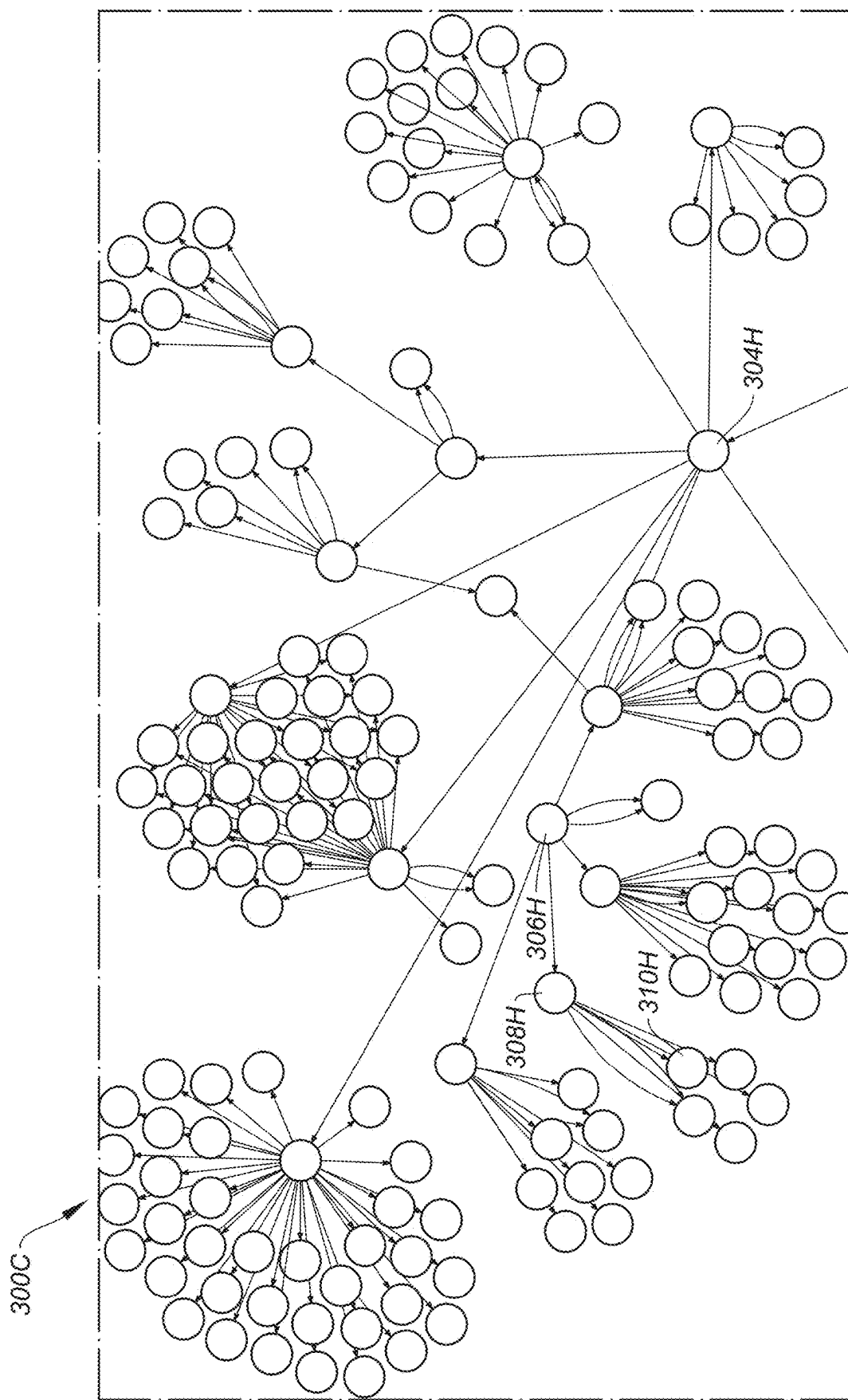


FIG. 5

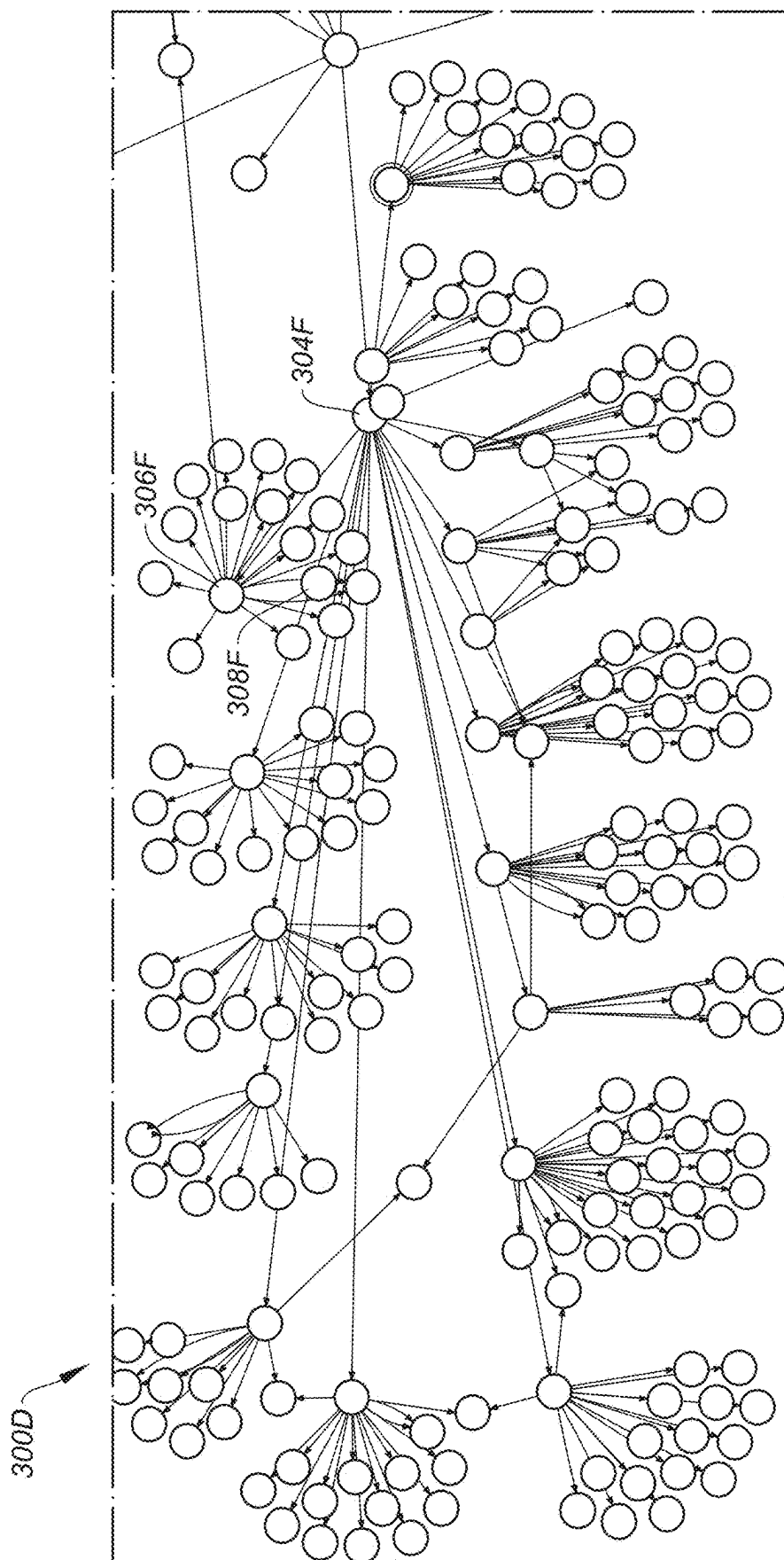


FIG. 6

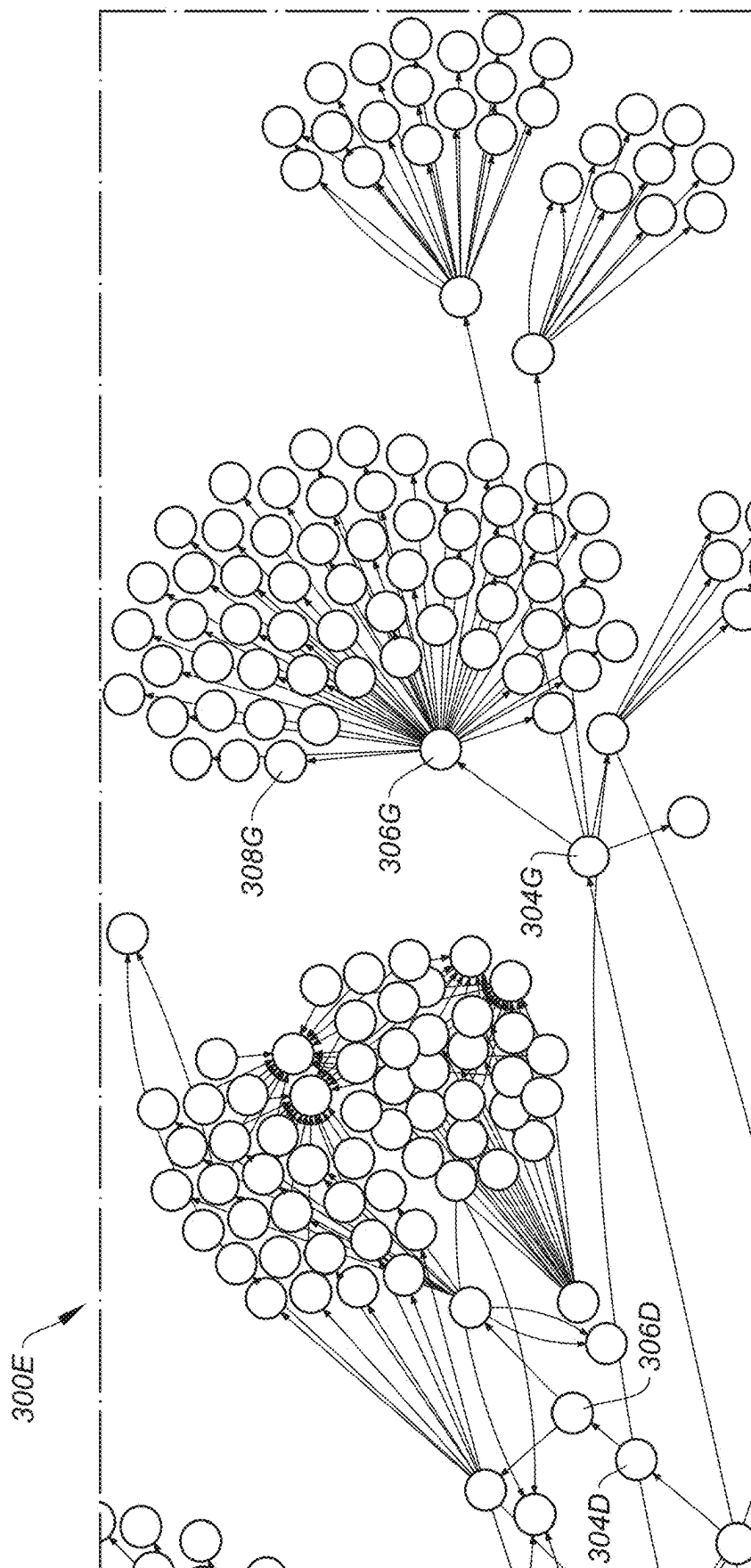


FIG. 7

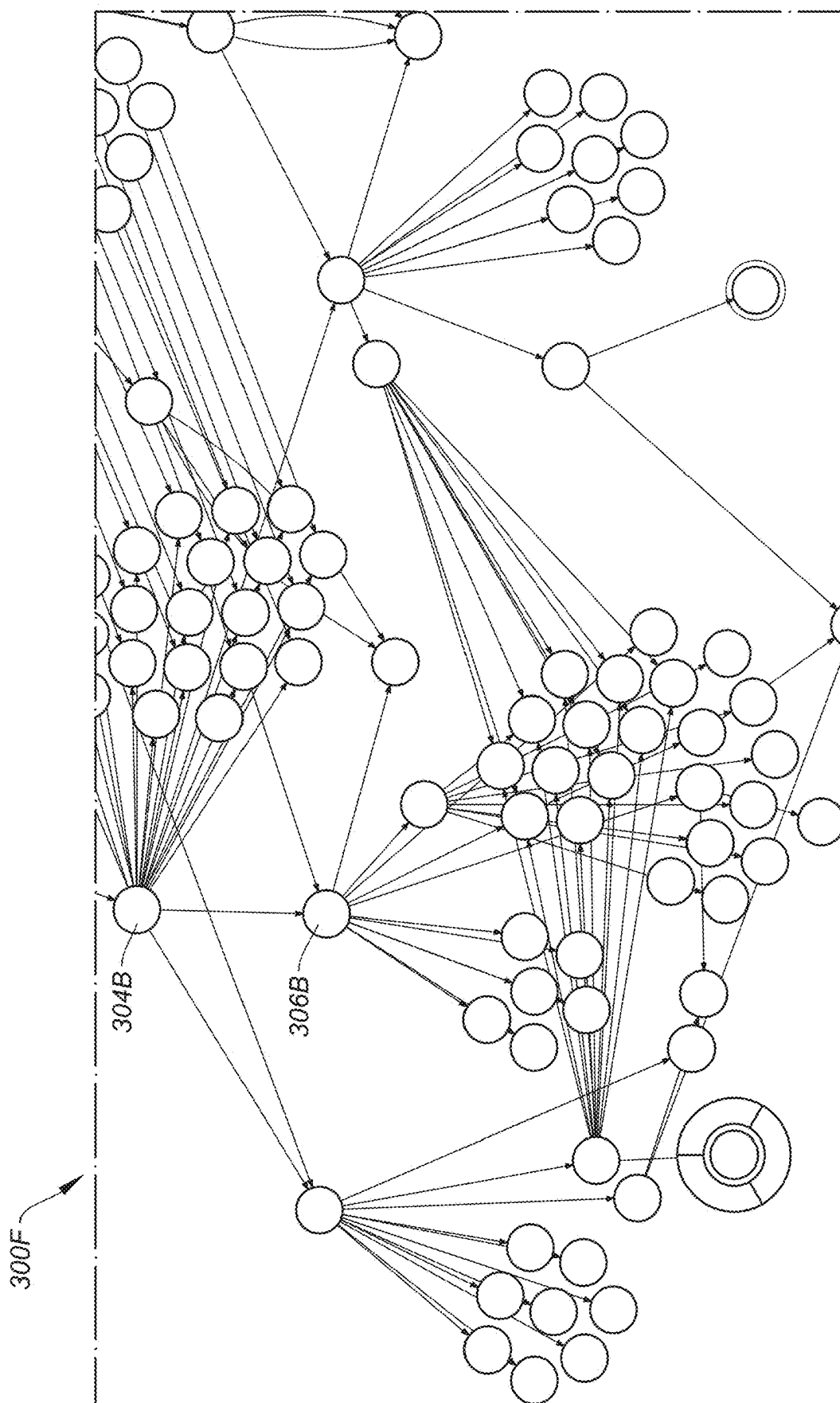


FIG. 8

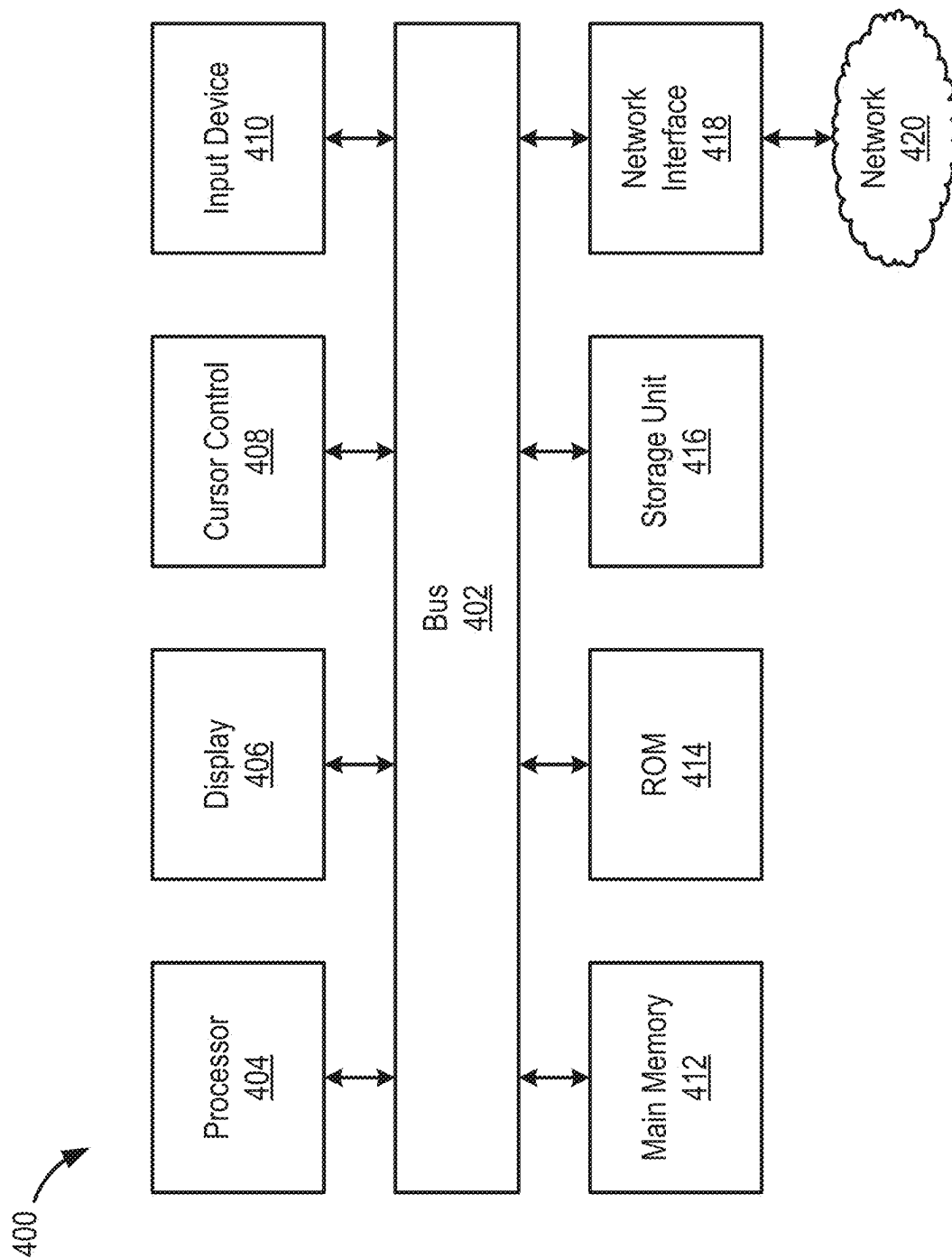


Fig. 9

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SYSTEMS AND METHODS FOR AUTOMATED SCRIBES BASED ON KNOWLEDGE GRAPHS OF CLINICAL INFORMATION HAVING WEIGHTED CONNECTIONS

CROSS-REFERENCE TO RELATED APPLICATIONS

This application claims priority to Provisional Patent Application No. 63/150,993, filed Feb. 18, 2021, which is incorporated herein by reference in its entirety for all purposes.

FIELD OF THE DISCLOSURE

The present disclosure relates to healthcare technology; and, more specifically, generating and/or applying a knowledge graph of clinical information.

BACKGROUND OF THE DISCLOSURE

The evolution of digital medicine has increased the demand for structured and concise clinical information to better access clinical quality, disease outcomes, and provider performance. As such, the demands for more granular, codified, and/or structured data has resulted in the increase in provider data entry burden through the use of complex software and/or data entry systems. In addition, the emergence of virtual assistants and semi-automated data capture systems often requires a clinical semantic network capable of formulating dialog and interpreting responses within the context of clinical knowledge. The human hardware and/or software interface is often a barrier to personalized care in many cases, and it has reduced the joy of practicing medicine and increased frustration among providers. Embodiments disclosed herein alleviate these issues.

SUMMARY OF THE DISCLOSURE

The present disclosure relates to rating and/or applying a knowledge graph of clinical information. Merely by way of example, the present disclosure has been applied to the field of medicine, but it would be recognized that the present disclosure has much broader range of applicability.

According to various embodiments, a computer-implemented method for, a system configured for, and a non-transitory computer-readable medium storing instructions when executed causes a processor to perform a set of operations including: identifying a clinical encounter associated with a clinical concern; representing the clinical concern as a module of a knowledge graph of clinical information; associating at least one section node with the module, each section node of the at least one section node corresponding to a clinical concept relevant to the clinical concern; associating, for each section node of the at least one section node, at least one topic node with the section node, each topic node of the at least one topic node corresponding to a clinical topic relevant to the corresponding clinical concept; and generating the knowledge graph of clinical information to represent the clinical concern, the relevant clinical concepts, and the relevant clinical topics; wherein associating the at least one section node with the module comprises: determining, for each section node, a concept relevancy between the corresponding clinical concept and the clinical concern; and representing the concept relevancy

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by the weightings of the connections between the section nodes and the module.

BRIEF DESCRIPTION OF THE DRAWINGS

The features of this disclosure, and the manner of attaining them, will become more apparent and the disclosure itself will be better understood by reference to the following description of embodiments of the disclosure taken in conjunction with the accompanying drawings. In the figures, like reference numerals represent like elements, and the figures are to be understood as illustrative of the disclosure. The figures are not necessarily drawn to scale and are not intended to be limiting in any way.

FIG. 1 is a simplified block diagram showing a system for generating and/or applying a knowledge graph of clinical information, according to various embodiments of the present disclosure.

FIG. 2A is a simplified flow diagram showing a method for generating and/or applying a knowledge graph of clinical information, according to various embodiments of the present disclosure.

FIG. 2B is a simplified flow diagram showing another method for generating and/or applying a knowledge graph of clinical information, according to various embodiments of the present disclosure.

FIG. 3 illustrates a module node and section nodes of a knowledge graph of clinical information, according to certain embodiments of the present disclosure.

FIG. 4 illustrates topic nodes associated with section nodes of a knowledge graph of clinical information, according to certain embodiments of the present disclosure.

FIG. 5 illustrates a section node pertaining to History of Present Illness (HPI) and related child nodes of a knowledge graph of clinical information, according to certain embodiments of the present disclosure.

FIG. 6 illustrates a section node pertaining to Review of Systems and related child nodes of a knowledge graph of clinical information, according to certain embodiments of the present disclosure.

FIG. 7 illustrates section nodes pertaining to Exam and Histories and related child nodes of a knowledge graph of clinical information, according to certain embodiments of the present disclosure.

FIG. 8 illustrates a section node pertaining to Care Plans and related child nodes of a knowledge graph of clinical information, according to certain embodiments of the present disclosure.

FIG. 9 is a simplified block diagram showing a computer system configured for generating and/or applying a knowledge graph of clinical information, according to various embodiments of the present disclosure.

While the present disclosure is amenable to various modifications and alternative forms, specific embodiments have been shown by way of example in the drawings and are described in detail below. The intention, however, is not to limit the present disclosure to the particular embodiments described. On the contrary, the present disclosure is intended to cover all modifications, equivalents, and alternatives falling within the scope of the present disclosure as defined by the appended claims.

DETAILED DESCRIPTION

In the following detailed description, reference is made to the accompanying drawings which form a part hereof, and in which is shown by way of illustration specific embodi-

ments in which the present disclosure is practiced. These embodiments are described in sufficient detail to enable those skilled in the art to practice the present disclosure, and it is to be understood that other embodiments can be utilized and that structural changes can be made without departing from the scope of the present disclosure. Therefore, the following detailed description is not to be taken in a limiting sense, and the scope of the present disclosure is defined by the appended claims and their equivalents.

Reference throughout this specification to “one embodiment,” “an embodiment,” or similar language means that a particular feature, structure, or characteristic described in connection with the embodiment is included in at least one embodiment of the present disclosure. Appearances of the phrases “in one embodiment,” “in an embodiment,” and similar language throughout this specification may, but do not necessarily, all refer to the same embodiment. Similarly, the use of the term “implementation” means an implementation having a particular feature, structure, or characteristic described in connection with one or more embodiments of the present disclosure, however, absent an express correlation to indicate otherwise, an implementation may be associated with one or more embodiments. Furthermore, the described features, structures, or characteristics of the subject matter described herein may be combined in any suitable manner in one or more embodiments.

As the terms are used herein with respect to ranges of measurements (such as those disclosed immediately above), “about” and “approximately” may be used, interchangeably, to refer to a measurement that includes the stated measurement and that also includes any measurements that are reasonably close to the stated measurement, but that may differ by a reasonably small amount such as will be understood, and readily ascertained, by individuals having ordinary skill in the relevant arts to be attributable to measurement error, differences in measurement and/or manufacturing equipment calibration, human error in reading and/or setting measurements, adjustments made to optimize performance and/or structural parameters in view of differences in measurements associated with other components, particular implementation scenarios, imprecise adjustment and/or manipulation of objects by a person or machine, and/or the like.

Although the term “block” may be used herein to connote different elements illustratively employed, the term should not be interpreted as implying any requirement of, or particular order among or between, various steps disclosed herein unless and except when explicitly referring to the order of individual steps. Additionally, a “set” or “group” of items (e.g., inputs, algorithms, data values, etc.) may include one or more items, and, similarly, a subset or subgroup of items may include one or more items.

As stated above, the demands for more granular, codified and/or structured data has resulted in the increase in provider data entry burden through the use of complex software and/or data entry systems, in at least some embodiments. As an example, the human hardware and/or software interface is a barrier to personalized care in many cases, and it has reduced the joy of practicing medicine and increased the frustration of providers. In addition, the emergence of virtual assistants and semi-automated data capture systems requires a clinical semantic network capable of formulating dialog and interpreting responses within the context of clinical knowledge.

According to certain embodiments, one approach to mitigating the complex data entry tasks and reducing burnout has been the use of live scribes-assistants that monitor and

manage all the data entry tasks for the provider. While this approach has its benefits, it is often not automated, and this usually cannot reach highly efficient economies of scale, in certain embodiments. By fully automating the live scribe’s function, one may be able to reduce provider burnout while decreasing the total cost of healthcare, given the relative efficiencies afforded to the provider when offsetting data entry tasks, according to certain embodiments.

According to certain embodiments, with the acceleration of machine learning and natural language processing, automated scribe technologies are leveraged to improve physicians’ lives with an ambient solution to automate clinical documentation, significantly reducing this administrative burden which occupies nearly half their working time. According to certain embodiments of the present disclosure, a knowledge graph of clinical information is generated to facilitate automated scribe technology. In at least some instances, the knowledge graph of clinical information has a variety of use cases including, but not limited to, diagnosis decision support, automated current procedural terminology (CPT) determination and information of classifications of diseases-10 (ICD-10) coding, and care plan decision support.

FIG. 1 is a simplified block diagram showing a system **100** for generating and/or applying a knowledge graph of clinical information, according to certain embodiments of the present disclosure. This figure is merely an example, which should not unduly limit the scope of the claims. One of ordinary skill in the art would recognize many variations, alternatives, and modifications. The system **100** includes a server **102**, one or more user devices **104**, one or more other servers **106**, and a network **108**. In various examples, system **100** includes one or more processors and a memory storing instructions that, upon execution by the one or more processors, cause the computing system to perform one or more processes including one or more processes of method **200** of FIG. 2A and/or method **250** of FIG. 2B. Although the above has been shown using a selected group of components, there can be many alternatives, modifications, and variations. In some examples, some of the components may be expanded and/or combined. Some components may be removed. Other components may be inserted to those noted above. Depending upon the embodiment, the arrangement of components may be interchanged with others replaced. In certain embodiments, the knowledge graph of clinical information is used by and/or incorporated into an automated scribe technology, as discussed in more detail below.

According to certain embodiments, the system **100** includes a server **102** that is configured to generate a knowledge graph of clinical information. While only one server **102** is depicted, the server **102** may comprise of multiple servers.

According to certain embodiments, the server **102** stores and/or receives, from one or more user devices **104** or another server **106** via a network **108**, a problem-oriented clinical knowledgebase **110**. User devices **104** may include, but are not limited to, smart devices (e.g., phones, watches, speakers, etc.), computers, televisions, set-top boxes, and/or the like. The network **108** may be, or include, any number of different types of communication networks such as, for example, a bus network, a short messaging service (SMS), a local area network (LAN), a wireless LAN (WLAN), a wide area network (WAN), the Internet, a P2P network, custom-designed communication or messaging protocols, and/or the like. The network **108** may include a combination of multiple networks.

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In certain instances, the problem-oriented clinical knowledgebase **110** is designed to serve as a source of content underlying a knowledge graph of clinical information **112**, which can be used by and/or incorporated into virtual scribe technology. In some examples, this problem-oriented clinical knowledgebase **110** contains codified clinical concepts and relationships that follow clinical evidence-based best practices. For example, these codified clinical concepts and relationships are curated by clinical and informatics experts, based on published standards of care. As examples, relating concepts in this way furthers the virtual scribe technology as follows:

1. serves as a reference base of anticipated clinical concepts and their relationships to the encounter process and current topic of conversation (e.g., clinical complaint) to improve the performance of natural language understanding algorithms; and/or
2. serves as machine learning training data, to include but not limited to:
 - a. feature data that consists of conversational text, which may include marked-up or tagged using natural language processing (NLP); and/or
 - b. feature data that consists of the current state of an instantiated knowledge graph of clinical information, representing the sequential concepts expressed prior or just prior to current time within a given encounter or patient interview; and/or
 - c. label data which consists of the specific graph nodes representative of the current input conversational text; and/or
3. establishes an initial model of clinical understanding that can be expanded upon and/or tuned via real world use and serves as a basis for continuous learning and performance tuning; according to certain embodiments, the expansion and/or tuning may be based upon but is not limited to:
 - a. specific user historical use of the graph for a given problem—in this form of tuning, the user's past graph states may be used to weight the connections in the graph network (i.e., to train the machine learning (ML) model); for example, the system may be tuned to a particular user's pattern of use of the graph to help improve performance for that specific user; and/or
 - b. historical use across a broader set of users to identify gaps in the graph that may serve to improve overall robustness for all users; and/or
4. provides sentence structure to aid in the generation of appropriate clinical narrative relative to the concepts expressed; and/or
5. supports the use of custom reference models that are provider-specific, including custom macros and helpers that reflect individual preferences related to intake, encounter flow and narrative output; and/or
6. enables real-time feedback as to clinical completeness and compliance with standards of care for a given complaint history or relevant plan of care.

According to certain embodiments, a technical barrier is addressed to achieving a fully automated scribe, which is, for example, called a virtual scribe, by the generation and/or application of a knowledge graph of clinical information **112**, as described herein. As an example, an automated virtual scribe solution is comprised of a passive listening device that can separate speakers, identify questions and answers, and reduce a conversation to a set of related key concepts. In certain instances, these concepts, need context in terms of their relevance to the clinical concern, their

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relationship to the standard of care for a given problem or concern, and/or their relationship to the encounter and the resulting clinical document that is produced as a result of the clinical encounter. The knowledge graph of clinical information **112**, as described herein, provides that context. In certain instances, the knowledge graph of clinical information **112** is referred to herein as the knowledge graph **112**.

In certain embodiments, the knowledge graph **112** includes a set of nodes and relationships that each have specific attributes that form a clinical reference for a given clinical concern within the context of a clinical encounter. As an example, the nodes of the knowledge graph **112** are organized around a given clinical concern and/or encode the expected clinical concepts that are expressed within an encounter, their relevance, related ontology and/or codification, hierarchy, sequence and/or related expression with respect to the encounter document.

In certain embodiments, the nodes of the knowledge graph **112** are organized as modules. For example, each module is related to a given clinical concern or problem, and/or includes an array of associated keywords, diagnoses and/or affiliated specialties. As an example, the children sections (also referred to herein as section nodes, topic nodes, sub-topic nodes, attribute nodes and/or concept nodes) within a module reflect the sequential steps within an encounter and/or the sequential groups of concepts within each step that are related to the standard of care and common practice of medicine. As such, in certain examples, each clinical concept in turn is indexed to one or to many relevant clinical ontologies via its representative code or codes. In certain embodiments, the common form of expression of the clinical sections or subsections and/or concepts is also included as an attribute of each node if applicable.

In some embodiments, the resulting knowledge graph **112** creates a searchable referential map of medical knowledge and/or standards of care. For example, by structuring the information as a graph or contained within a graph database, inbound patterns of concepts generated by a natural language processing (NLP) pipeline of an automated virtual scribe system and/or generated by an engine for natural language understanding (NLU) of the automated virtual scribe system are matched to the knowledge graph **112** to yield one or more following results by the automated virtual scribe system:

1. a ranked order of modules that conform to the input pattern; and/or
2. a determination of matched concepts that link the actual input to the expected input; and/or
3. a narrative output resulting from the union of the matched concepts and steps and their associated expression attributes; and/or
4. a confirmed set of codified and structured clinical concepts and/or data determined from the conversation of the clinical concept, which can be communicated to clinical software systems in real time to trigger clinical decision support modules, and/or be stored for use later in chart communication, quality assessments and/or data analytics applications; and/or
5. a set of codified clinical data determined from clinical notes, other documents, and/or free text conversion, which can be used for knowledge extraction; and/or
6. determine and/or drive chat bot dialog questions in order to suggest and/or codify likely responses.

In certain embodiments, an automated virtual scribe system includes: (i) a passive listening device that separates speakers, identifies questions and answers, and reduces a conversation to a set of related key concepts; (ii) a database

that stores a knowledge graph **112** (and/or, e.g., a knowledge graph **300** as shown in FIGS. **3-8**); (iii) transforms the conversation to a set of tagged words, expressions and/or organized narrative; (iv) maps the conversation (e.g., the set of tagged words, expressions and/or organized narrative) to the knowledge graph **112** (and/or knowledge graph **300**), and/or (v) the server **102** that receives the set of related key concepts, uses the stored knowledge graph **112** (and/or, e.g., a knowledge graph **300**), and generates the one or more results as described above and/or generates one or more other results (e.g., the results provided in blocks **216-224**).

FIG. **2A** is a simplified flow diagram showing a method **200** for generating a knowledge graph, according to certain embodiments of the present disclosure. This figure is merely an example, which should not unduly limit the scope of the claims. One of ordinary skill in the art would recognize many variations, alternatives, and modifications. In certain examples, method **200** is configured to be implemented by system **100** of FIG. **1**. In various examples, method **200** includes representing a clinical concern as a module of a knowledge graph (block **202**), associating a section node with the module (block **204**), associating a topic node with the section node (block **206**), associating a sub-topic node with the topic node (block **208**), associating an attribute node with the sub-topic node (block **210**), outputting the knowledge graph (block **212**), mapping raw data of a clinical encounter to the knowledge graph (block **214**), determining whether population health analytics can be performed (block **216**), determining whether a clinical quality measurement can be calculated (block **218**), scoring the electronic health record documentation (block **220**), generating electronic health record documentation (block **222**), and/or adapting the map of the raw data to the knowledge graph (block **224**). Although the above has been shown using a selected group of processes for the method, there can be many alternatives, modifications, and variations. In some examples, some of the processes may be expanded and/or combined. Other processes may be inserted to those noted above. Depending upon the embodiment, the sequence of processes may be interchanged with others replaced. In some examples, some or all processes of the method are performed by a computing system or a processor directed by instructions stored in memory. As an example, some or all processes of method **200** are performed according to instructions stored in a non-transitory computer-readable medium.

FIG. **2B** is a simplified flow diagram showing another method **250** for generating a knowledge graph, according to certain embodiments of the present disclosure. This figure is merely an example, which should not unduly limit the scope of the claims. One of ordinary skill in the art would recognize many variations, alternatives, and modifications. In certain examples, method **250** is configured to be implemented by system **100** of FIG. **1**. In some examples, one or more processes of method **200** and one or more processes of method **250** may be interchanged, incorporated, or removed. In various examples, method **250** includes identifying (or receiving, obtaining, such as from a user input) a clinical encounter associated with a clinical concern (block **252**), representing the clinical concern as a module (block **254**), associating at least one section node with the module (block **256**), associating at least one topic node with the section node (block **258**), generating the knowledge graph of clinical information (block **260**). In some examples, method **250** further includes transmitting the knowledge graph (e.g., to a user device or server), or presenting the knowledge graph (e.g., via a graphical user interface (GUI)). Although the above has been shown using a selected group of processes

for the method, there can be many alternatives, modifications, and variations. In some examples, some of the processes may be expanded and/or combined. Other processes may be inserted to those noted above. Depending upon the embodiment, the sequence of processes may be interchanged with others replaced. In some examples, some or all processes of the method are performed by a computing system or a processor directed by instructions stored in memory. As an example, some or all processes of method **250** are performed according to instructions stored in a non-transitory computer-readable medium.

As illustrated, the method **200** includes representing a clinical concern as a module of the knowledge graph (block **202**) and associating at least one section node with the module, wherein each section node of the at least one section node corresponds to a clinical concept relevant to the clinical concern (block **204**).

According to certain embodiments, the knowledge graph includes the relevancy of a node included in the knowledge graph to a diagnosis. In some examples, the relevancy of a node to a diagnosis is expressed by a weighting. In certain embodiments, the weighting can be between a node and a diagnosis generally or between two specific nodes in the knowledge graph. The relevancy of each of the nodes to a diagnosis can be used during automated ICD-10 coding and/or for use by a virtual assistant. While weighting of a connection is provided as an example for an indicator or parameter that may be used to show relevancy, it is to be understood that other indicators or parameters are contemplated as well (e.g., color, transparency, line-brokenness).

For example, associating the at least one section node with the module includes determining a relevancy between the at least one section node and the module. In some aspects, the relevancy can include, but is not limited to, specificity, sensitivity, probability, and/or prevalence. In some embodiments, the relevancy can be expressed as a weighting between the module and the at least one section node that signifies how closely related the module is to the at least one section node, such that a higher weighting corresponds to a closer relationship between the at least one section node and a module than a lower weighting. In at least one example, to determine a relevancy, the method **200** queries a table that includes relevancy information between a module and a section node. For example, method **200** can query a table that provides probabilities of relationships during clinical encounters. The probabilities can be based on statistical analysis of clinical encounters that indicate for a given module the different section nodes that the module may be associated with and how often the module is associated with each section node. These probabilities can be used as the relevancy (e.g., a weighting) between an associated module and section node. While weighting of a connection is provided as an example for an indicator or parameter that may be used to show relevancy, it is to be understood that other indicators or parameters are contemplated as well (e.g., color, transparency, line-brokenness).

In certain embodiments, the nodes of the knowledge graph (e.g., the knowledge graph **112**) are organized by relationships, and a fundamental relationship that segregates the knowledge graph (e.g., the knowledge graph **112**) is the clinical concern. As such, the knowledge graph (e.g., the knowledge graph **112**) can be considered a problem-oriented knowledge graph with each problem consisting of a sub-graph, called a module, such that each module is based upon a particular clinical problem or concern.

FIG. **3** illustrates an example of a clinical concern, e.g., knee pain, being represented as a module **302**, which is the

central node a knowledge graph **300A**. This diagram is merely an example, which should not unduly limit the scope of the claims. One of ordinary skill in the art would recognize many variations, alternatives, and modifications.

According to certain embodiments, the portion of the knowledge graph **300A** and other portions of the knowledge graph **300B-300F** collectively form the knowledge graph **300** for a particular clinical concern, e.g., knee pain. And, the knowledge graphs **300** associated with each clinical concern collectively form the knowledge graph **112**, in certain embodiments. Other examples of clinical concerns besides knee pain include, but are not limited to, hip pain, back pain, chest pain, skin rash, and/or fainting.

In certain embodiments, the knowledge graph **112** as a whole, and each knowledge graph **300** associated with a particularly clinical concern, are comprised of related nodes, each node representing hierarchically organized clinical concepts relevant to the clinical concern of the module **302** included in the associated knowledge graph **300**. In certain embodiments, each module (e.g., module **302**) and its related child nodes included in a knowledge graph for a particular clinical concern (e.g., the knowledge graph **300**) is built to reflect a typical sequence and structure of a clinical encounter through additional relationships that organize relevant nodes. As such, in certain examples, each knowledge graph for a particular clinical concern (e.g., the knowledge graph **300**) is generated, expanded, and/or updated using data from encounters between patients and providers.

In some examples, the knowledge graph **112** and each knowledge graph for a particular clinical concern (e.g., the knowledge graph **300**) is generated, expanded, and/or updated from recognized standards of care, published practice guidelines, clinical quality metrics, other sources of published clinical information, including general physician knowledge. In certain instances, these sources change by, for example, being updated, increasing in scope, and sometimes retracted. As such, the knowledge graph **112** and each knowledge graph for a particular clinical concern (e.g., the knowledge graph **300**) changes over time in response to the sources of the data changing, according to at least some embodiments.

Additionally, or alternatively, in some examples, raw data from a clinical encounter is mapped to a knowledge graph for a particular clinical concern (e.g., the knowledge graph **300**) using, for example, a neural network to determine: (i) the nodes of a knowledge graph (e.g., the knowledge graph **300**) pertaining to a particular clinical encounter, (ii) and/or a sequence of the nodes for a particular clinical encounter.

In the example illustrated in FIG. 3, the clinical concern and/or chief complaint represented by the module **302** is knee pain. In certain embodiments, the next set of relationships are hierarchal and are shown as section nodes **304A-304H** of the encounter flow. As such, in certain embodiments, the module **302** is associated with at least one section node **304A-304H**. The sections nodes **304A-304H** include, for example, Diagnoses **304A**, Care Plans **304B**, Demographic information **304C**, Examination **304D**, Vitals **304E**, Review of Systems (RoS) **304F**, Patient History (Medical, Social, Surgical, Family, etc.) (PMSFH) **304G**, and/or History of Present Illness (HPI) **304H**.

In certain embodiments, the method **200** includes associating each section node **304A-304H** with at least one topic node **306A-306H** (block **206**). Each of the at least one topic node **306A-306H** is a clinical topic that relates to the encounter for a clinical concern. While clinical encounter structure and/or order may vary based on the type of encounter and/or clinical concern being addressed, in certain

embodiments, there is a limited set of section nodes **304A-304H** and/or topic nodes **306A-306H** that can categorize the content of clinical encounters.

In certain instances, associating each section node with at least one topic node includes determining a relevancy between a section node and the at least one topic node. In some aspects, the relevancy can include, but is not limited to, specificity, sensitivity, probability, and/or prevalence. In some embodiments, the relevancy can be expressed as a weighting between the section node and the at least one topic node that signifies how closely related the section node is to the at least one topic node, such that a higher weighting corresponds to a closer relationship between the section node and the at least one topic node than a lower weighting. In at least one example, to determine a relevancy, the method **200** queries a table that includes relevancy information between a section node and a topic node. For example, method **200** can query a table that provides probabilities of relationships during clinical encounters. The probabilities can be based on statistical analysis of clinical encounters that indicate for a given section node the different topic nodes that the section node may be associated with and how often the section node is associated with each topic node. These probabilities can be used as the relevancy (e.g., a weighting) between an associated section node and topic node. While weighting of a connection is provided as an example for an indicator or parameter that may be used to show relevancy, it is to be understood that other indicators or parameters are contemplated as well (e.g., color, transparency, line-brokenness).

Examples of topic nodes **306A-306H** associated with each section node **304A-304H** are illustrated in FIGS. 4-8. For example, FIG. 4 illustrates an example of topic nodes **306A-306H** associated with section nodes **304A-304H** of a knowledge graph **300**; FIG. 5 illustrates an example of a section node **304H** pertaining to HPI and related child nodes of a knowledge graph **300**; FIG. 6 illustrates an example of a section node pertaining to RoS **304F** and related child nodes of a knowledge graph; FIG. 7 illustrates examples of section nodes **304D**, **304G** pertaining to Exam and Histories and related child nodes of a knowledge graph; and, FIG. 8 illustrates an example of a section node **304B** pertaining to Care Plans and related child nodes of a knowledge graph.

In certain examples, each section node **304A-304H** and/or topic node **306A-306H** has an assigned index which represents their anticipated sequence order over time. Thus, for example, the knowledge graph **300** captures many data relationships including anticipated sequence of the concepts over time for a given encounter. For example, in the HPI section node **304H**, the several topic nodes **306H** that are associated with the HPI section node **304H** are common areas of interrogation and/or are symptoms and/or signs that relate to the HPI, such as onset, location, pain, alleviating factors, aggravating factors, timing, reason for visit, etc. As another example, the Diagnosis section node **304A**, can include several topic nodes **306A** that are used to represent a clinical diagnosis such as “knee sprain” or “anterior cruciate ligament injury”.

According to certain embodiments, the method **200** includes associating each topic node (e.g., one or more of the topic nodes **306A-306H**) with at least one sub-topic node (e.g., sub-topic node **308F**, **308G** and/or **308H**) (block **208**). Additionally, or alternatively, each sub-topic node can be directly associated with a section node (e.g., one or more of the section nodes **304A-304H**) when, for example, a typical clinical encounter progresses from a section node (e.g., one

or more of the section nodes **304A-304H**) directly to a sub-topic node (e.g., sub-topic **308F**, **308G** and/or **308H**).

In certain instances, associating each topic node with at least one sub-topic node includes determining a relevancy between a topic node and the at least one sub-topic node. In some aspects, the relevancy can include, but is not limited to, specificity, sensitivity, probability, and/or prevalence. In some embodiments, the relevancy can be expressed as a weighting between the topic node and the at least one sub-topic node that signifies how closely related the topic node is to the at least one sub-topic node, such that a higher weighting corresponds to a closer relationship between the topic node and the at least one sub-topic node than a lower weighting. In at least one example, to determine a relevancy, the method **200** queries a table that includes relevancy information between a topic node and a sub-topic node. For example, method **200** can query a table that provides probabilities of relationships during clinical encounters. The probabilities can be based on statistical analysis of clinical encounters that indicate for a given topic node the different sub-topic nodes that the topic node may be associated with and how often the topic node is associated with each sub-topic node. These probabilities can be used as the relevancy (e.g., a weighting) between an associated topic node and sub-topic node. While weighting of a connection is provided as an example for an indicator or parameter that may be used to show relevancy, it is to be understood that other indicators or parameters are contemplated as well (e.g., color, transparency, line-brokenness).

In certain embodiments, each sub-topic node (e.g., sub-topic node **308F**, **308G** and/or **308H**) can be a finding of a query associated with the topic node (e.g., one or more of the topic nodes **306A-306H**), such as the actual onset timing, or anatomical location of the complaint. In the case of knee pain, for example, the onset can be “sudden” and the location can be “left knee”. As another example, in the case of leg pain, the location can be patella, distal femur, neck of tibia, etc. In certain embodiments, this hierarchical relationship between symptom/sign and findings continues across the various nodes e.g., one or more of the nodes **302A-310H**) and organizes the concepts into common collections, that are consistent with encounter flow.

According to certain embodiments, the method **200** includes associating each sub-topic node (e.g., sub-topic node **308F**, **308G** and/or **308H**) with at least one attribute node (e.g., attribute node **310H**) (block **210**). Additionally, or alternatively, each attribute node (e.g., attribute node **310H**) can be directly associated with a topic node (e.g., one or more of the topic nodes **306A-306H**) when, for example, a typical clinical encounter progresses from a topic node (e.g., one or more of the topic nodes **306A-306H**) directly to an attribute node (e.g., attribute node **310H**). In certain embodiments, the at least one attribute node (e.g., attribute node **310H**) is associated with multiple section nodes (e.g., multiple of the section nodes **304A-304H**), topic nodes (e.g., the topic nodes **306A-306H**), and/or sub-topic nodes (e.g., sub-topic node **308F**, **308G** and/or **308H**) across the knowledge graph **300**, in the event the at least one attribute node (e.g., attribute node **310H**) is relevant to multiple section nodes (e.g., multiple of the section nodes **304A-304H**), topic nodes (multiple of the topic nodes **306A-306H**), and/or sub-topic nodes (e.g., sub-topic node **308F**, **308G** and/or **308H**).

In certain instances, associating each sub-topic node with at least one attribute node includes determining a relevancy between a sub-topic node and the at least one attribute node. In some aspects, the relevancy can include, but is not limited

to, specificity, sensitivity, probability, and/or prevalence. In some embodiments, the relevancy can be expressed as a weighting between the sub-topic node and the at least one attribute node that signifies how closely related the sub-topic node is to the at least one attribute node, such that a higher weighting corresponds to a closer relationship between the sub-topic node and the at least one attribute node than a lower weighting. In at least one example, to determine a relevancy, the method **200** queries a table that includes relevancy information between a sub-topic node and an attribute node. For example, method **200** can query a table that provides probabilities of relationships during clinical encounters. The probabilities can be based on statistical analysis of clinical encounters that indicate for a given sub-topic node the different attributes nodes that the sub-topic node may be associated with and how often the sub-topic node is associated with each attribute node. These probabilities can be used as the relevancy (e.g., a weighting) between an associated sub-topic node and attribute node. While weighting of a connection is provided as an example for an indicator or parameter that may be used to show relevancy, it is to be understood that other indicators or parameters are contemplated as well (e.g., color, transparency, line-brokenness).

Examples of attributes represented by an attribute node (e.g., attribute node **310H**) include, but are not limited to, left, right, neither, none, etc.

In some embodiments, one attribute of note is the textual representation for the node and its children. For example, the “onset” node mentioned above has an encoded textual attribute such as “The patient reports the <symptom> was <findings>” that is used to generate narrative in a prose that is easy to understand and is consistent with medical documentation convention.

According to certain embodiments, the method **200** includes associating one or more concept nodes with one or more of the other nodes (e.g., the nodes **302-310H**) of the knowledge graph **300**. In some embodiments, concept nodes represent a particular clinical concept, or other information, including, for example, specific diagnoses, procedures, medications, allergies, demographic, or clinically relevant social information. In certain embodiments, concept nodes are modified by attributed nodes, and will typically be associated with particular standard clinical code systems or ontologies. For example, wrist pain, as represented by node **308F** would be an example of a granular clinical concept, that can be modified by attributes (e.g., left or right), but would not necessarily be a parent node to multiple other concepts.

In certain embodiments, one or more of the nodes (e.g., one or more of the nodes **302-310H**) are associated with a codified node that corresponds to codified values of the concept in various taxonomies and/or ontologies, giving the node nodes (e.g., one or more of the nodes **302-310H**) additional relationships and related concepts that are useful in finding synonyms and/or other useful properties of the codified concept.

According to some embodiments, different color nodes represent different layers (e.g., section nodes, topic, nodes, sub-topic nodes, and/or attribute nodes) of the knowledge graph **300**.

According to certain embodiments, the method **200** includes outputting the knowledge graph **300** to, for example, a user device **104** (block **212**).

As discussed above, in certain embodiments, the knowledge graph **112** and/or the portion of the knowledge graph **300** represents a reference set of clinically relevant concepts

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and relationships to a given concern. As such, according to certain embodiments, the method 200 includes mapping raw data of a clinical encounter to the knowledge graph 112 and/or 300 to semantically represent the contents of the clinical encounter (block 214). For example, for a clinical encounter, the knowledge graph 112 and/or 300 is used by an automated virtual scribe system to compare sequential output from a NLP pipeline of the automated virtual scribe system and organize these concepts in their natural relationship to the module 302 pertaining to a particular clinical concern, the section 304A-304H and/or position in the encounter flow which they are recorded for a clinical encounter, as well as their identification with respect to clinical ontologies and/or taxonomies. Stated another way, in some embodiments, a neural network is used to map the raw data from a clinical encounter to one or more of the knowledge graphs 112 and/or 300. According to certain embodiments, the neural network (e.g., a recurrent neural network (RNN)) uses sequence data from the clinical encounter in order to map the clinical encounter to the knowledge graph 300. For example, NLP software may receive and process correspondence between a provider and a patient where the patient is complaining about right knee pain. In response to the right knee pain, the provider may ask what part of the patient's right knee hurts. In one example, the patient may state the medial aspect of the patient's knee hurts. In another example, the patient may state the lateral aspect of patient's knee hurts. In practice, these different examples may result in different mappings of the clinical encounter to the knowledge graph 300. As such, in some examples, the neural network may use, as an input for one or more layers of the neural network, prior answers to inform latter connections between nodes in the neural network so that appropriate diagnosis and treatment can be rendered.

In some instances, the mapping of the raw data of a clinical encounter to the knowledge graph (e.g., knowledge graph 112 and/or 300) by, for example, a machine learning algorithm, determines the state of the knowledge graph (e.g., knowledge graph 112 and/or 300) that includes the encounter sequence context, which can be used to predict the conversational conceptual expression. For example, the state of the knowledge graph (e.g., knowledge graph 112 and/or 300) in one embodiment could be a numerical representation of selected or mapped nodes (e.g., the nodes 302A-310H), based on encounter conversation content. This numerical representation could be expressed as a path, which is a series of numbers that represent the selected node (e.g., the nodes 302A-310H) with respect to hierarchical nodes (e.g., the nodes 302A-310H) and linking relationships. For example, an encounter that is concerned with knee pain is represented by the knowledge graph 300, such that the first few concepts expressed in conversation relates to the main symptom or complaint as knee pain, followed by pain location as right knee medial aspect, followed by associated swelling of right knee and aggravated pain on motion or weight bearing. The knowledge graph 300 state representation of this encounter may then be the paths for the nodes listed above. For example, each node path may be unique within the knowledge graph 300 and contain information that associates each selected node (e.g., the nodes 302A-310H) with the knee pain branch and related nodes (e.g., the nodes 302A-310H) that were selected in sequence. Thus, for example, the context of the chief complaint, in this case knee pain, and related children concepts are represented in sequential order as they occurred in the encounter. This context information may be used in other steps of the method 200, for example,

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blocks 216-224 of method 200, to gain insights into the clinical encounter that's not presented in the data, as set forth below.

According to certain embodiments, once a clinical encounter and/or clinical content is mapped to the knowledge graph 112 and/or 300, the knowledge graph 112 and/or 300 state can be analyzed to yield insights regarding various healthcare functions such as, for example, whether population health analytics can be performed (block 216); and, determining population health analytics in the event healthcare analytics can be performed.

In certain instances, given the knowledge graph (e.g., knowledge graph 112 and/or 300) is embodied in the form of an object or graph database, complex pattern matching is accomplished by the automated virtual scribe system to rank the input concepts from the NLP pipeline based on the predetermined fitting clinical module or concern. For example, in the setting where multiple problems are being discussed via natural conversation, the knowledge graph (e.g., knowledge graph 112 and/or 300) is used by the automated virtual scribe system to associate the grouped concepts with the appropriate clinical concern, problem, and/or complaint. In certain embodiments, this complex pattern matching feature of the knowledge graph (e.g., knowledge graph 112 and/or 300) is leveraged by the automated virtual scribe system in several use cases, such as clinical decision support as explained below.

In certain embodiments, given the knowledge graph (e.g., knowledge graph 112 and/or 300) represents the expected standard of care for the clinical concern, it is used by the NLP pipeline of the automated virtual scribe system to act as a filter to reject noise or irrelevant input and reduce error.

According to certain embodiments, the output of the NLP pipeline (e.g., the state of the graph, including the selected and unselected nodes) serves as an input to a checklist for what is expected and can be used by the virtual scribe system to interactively guide the conversation and ensure completeness of the encounter and data capture. For example, the ability of the NLP pipeline of the automated virtual scribe system to interactively prompt the clinician and guide the conversation or confirm input matches to the clinical reference model allows for the real time verification and error correction of computed data. As such, in some embodiments, the method 200 includes determining a whether clinical quality measurement can be calculated based on the state of the graph resulting from the mapping of the raw data of the clinical encounter to the knowledge graph of clinical information (block 218). And, in embodiments where the clinical quality measurement can be calculated, the method 200 can include determining a score of the quality of the clinical encounter.

Additionally, or alternatively, the method 200 includes scoring the generated electronic health record documentation to determine a completeness of a patient evaluation for the clinical encounter (block 220).

According to certain embodiments, the method 200 includes generating electronic health record documentation based on the mapping of the raw data of the clinical encounter to the knowledge graph (block 222). For example, once the conversation is complete and the output from the NLP pipeline is mapped to the knowledge graph (e.g., the knowledge graph 112 and/or 300) by the automated virtual scribe system, the state of the mapped knowledge graph (e.g., knowledge graph 112 and/or 300) represents the current codified and structured data of the clinical encounter and is thus in a highly computable and meaningful representation. In this state, the data model of the knowledge

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graph (e.g., knowledge graph 112 and/or 300) is transformed to conform with the data schemas of various information systems, such as electronic medical record systems, order entry systems, clinical decision support systems, and/or quality analytics systems, in at least some embodiments. Alternatively, the knowledge graph (e.g., knowledge graph 112 and/or 300) is iterated to produce a narrative expression of the data using the textual attributes of the relevant nodes to produce an accurate clinical note or document, in at least some embodiments.

According to certain embodiments, the method 200 includes adapting the mapping of the raw data of the clinical encounter to the knowledge graph to conform to a schema for the electronic health record and/or adapting the mapping of the raw data of the clinical encounter to the knowledge graph to conform to interoperability standards for health information technology systems (block 224). For example, given the section node 304A-304H, the method 200 can include determining if the encounter conversation is conducted out of expected sequence. The knowledge graph 300 can then be used by the automated virtual scribe system to match the output from the NLP that is "out of sequence" and generate a narrative that is "in sequence".

FIG. 9 is a simplified block diagram showing a computer system configured for generating and/or applying a knowledge graph, according to certain embodiments of the present disclosure. For example, some or all of the processes (e.g., steps) of the method 200 are performed by the computing system 400. This diagram is merely an example, which should not unduly limit the scope of the claims. One of ordinary skill in the art would recognize many variations, alternatives, and modifications.

The computing system 400 includes a bus 402 or other communication mechanism for communicating information between, a processor 404, a display 406, a cursor control component 408, an input device 410, a main memory 412, a read only memory (ROM) 414, a storage unit 416, and/or a network interface 418. In some examples, the bus 402 is coupled to the processor 404, the display 406, the cursor control component 408, the input device 410, the main memory 412, the read only memory (ROM) 414, the storage unit 416, and/or the network interface 418. And, in certain examples, the network interface 418 is coupled to a network 420 (e.g., the network 108).

In some examples, the processor 404 includes one or more general purpose microprocessors. In some examples, the main memory 412 (e.g., random access memory (RAM), cache and/or other dynamic storage devices) is configured to store information and instructions to be executed by the processor 404. In certain examples, the main memory 412 is configured to store temporary variables or other intermediate information during execution of instructions to be executed by processor 404. For example, the instructions, when stored in the storage unit 416 accessible to processor 404, render the computing system 400 into a special-purpose machine that is customized to perform the operations specified in the instructions (e.g., the method 200). In some examples, the ROM 414 is configured to store static information and instructions for the processor 404. In certain examples, the storage unit 416 (e.g., a magnetic disk, optical disk, or flash drive) is configured to store information and instructions.

In some embodiments, the display 406 (e.g., a cathode ray tube (CRT), an LCD display, or a touch screen) is configured to display information to a user of the computing system 400. In some examples, the input device 410 (e.g., alphanumeric and other keys) is configured to communicate information and commands to the processor 404. For

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example, the cursor control 408 (e.g., a mouse, a trackball, or cursor direction keys) is configured to communicate additional information and commands (e.g., to control cursor movements on the display 406) to the processor 404.

The invention can be further defined by one or more of the following aspects.

Aspect 1. A computer-implemented method for generating a knowledge graph of clinical information, the method comprising: identifying a clinical encounter associated with a clinical concern; representing the clinical concern as a module of a knowledge graph of clinical information; associating at least one section node with the module, each section node of the at least one section node corresponding to a clinical concept relevant to the clinical concern; associating, for each section node of the at least one section node, at least one topic node with the section node, each topic node of the at least one topic node corresponding to a clinical topic relevant to the corresponding clinical concept; and generating the knowledge graph of clinical information to represent the clinical concern, the relevant clinical concepts, and the relevant clinical topics; wherein associating the at least one section node with the module comprises: determining, for each section node, a concept relevancy between the corresponding clinical concept and the clinical concern; and representing the concept relevancies by the weightings of the connections between the section nodes and the module.

Aspect 2. The computer-implemented method of aspect 1, wherein the at least one clinical concept includes: history of present illness, review of systems, examination, history, diagnosis, or care plan.

Aspect 3. Any computer-implemented method of aspects 1-2, wherein the at least one clinical topic includes: onset, location, pain, alleviating factors, aggravating factors, timing, or reason for visit.

Aspect 4. Any computer-implemented method of aspects 1-3, wherein the concept relevancy includes: specificity, sensitivity, probability, or prevalence.

Aspect 5. Any computer-implemented method of aspects 1-4, wherein associating the at least one topic node with the section node comprises: determining, for each topic node and section node pair, a topic relevancy between the corresponding clinical topic and the corresponding clinical concept; and representing the topic relevancies by the weightings of the connections between the topic nodes and the section nodes.

Aspect 6. The computer-implemented method of aspect 5, wherein the topic relevancy includes: specificity, sensitivity, probability, or prevalence.

Aspect 7. Any computer-implemented method of aspects 1-6, further comprising associating, for each topic node of the at least one topic node, at least one sub-topic node with the topic node, wherein each sub-topic node of the at least one sub-topic node corresponds to a sub-topic to the corresponding clinical topic.

Aspect 8. The computer-implemented method of aspect 7, wherein associating the at least one sub-topic node with the topic node comprises: determining, for each sub-topic node and topic node pair, a sub-topic relevancy between the corresponding sub-topic and the corresponding clinical topic; and representing the sub-topic relevancies by the weightings of the connections between the sub-topic nodes and the topic nodes.

Aspect 9. The computer-implemented method of aspect 8, wherein the sub-topic relevancy includes: specificity, sensitivity, probability, or prevalence.

Aspect 10. Any computer-implemented method of aspects 7-9, further comprising associating, for each sub-topic node of the at least one sub-topic node, at least one attribute node to the sub-topic node, wherein each attribute node of the at least one attribute node corresponds to a qualifying attribute for the sub-topic.

Aspect 11. The computer-implemented method of aspect 10, wherein associating the at least one attribute node with the sub-topic node comprises: determining, for each attribute node and sub-topic node pair, an attribute relevancy between the corresponding qualifying attribute and the corresponding sub-topic; and representing the attribute relevancies by the weightings of the connections between the attribute nodes and the sub-topic nodes.

Aspect 12. The computer-implemented method of aspect 11, wherein the attribute relevancy includes: specificity, sensitivity, probability, or prevalence.

Aspect 13. Any computer-implemented method of aspects 10-12, wherein the knowledge graph of clinical information comprises a plurality of clinical concerns represented as a plurality of modules; and wherein the method further comprises associating an attribute node of the at least one attribute node with a sub-topic node associated with another clinical concern of the plurality of clinical concerns.

Aspect 14. The computer-implemented method of aspect 13, wherein the attribute node corresponds to at least one of the following attributes: left, right, both, and neither.

Aspect 15. Any computer-implemented method of aspects 1-14, wherein the association of the at least one section node with the module and the association of the at least one topic node with the at least one section node is based on at least one of the following: recognized standards of care, published practice guidelines, clinical quality metrics, other sources of published clinical information, and general physician knowledge.

Aspect 16. The computer-implemented method of aspect 15, further comprising updating the association of the at least one section node with the module and the association of the at least one topic node with the at least one section node when additional information from at least one of the following becomes available: the recognized standards of care, the published practice guidelines, the clinical quality metrics, the other sources of published clinical information, and the general physician knowledge.

Aspect 17. Any computer-implemented method of aspects 1-16, further comprising mapping raw data of a clinical encounter to the knowledge graph of clinical information resulting in a state of the knowledge graph pertaining to the clinical encounter.

Aspect 18. The computer-implemented method of aspect 17, further comprising using at least one of: machine learning and natural language processing to map the raw data of the clinical encounter to the knowledge graph of the clinical information.

Aspect 19. Any computer-implemented method of aspects 17-18, further comprising determining whether the state of the graph resulting from the mapping of the raw data of the clinical encounter to the knowledge graph of clinical information is sufficient to calculate a clinical quality measure.

Aspect 20. Any computer-implemented method of aspects 17-19, further comprising determining whether the state of the graph resulting from the mapping of the raw data of the clinical encounter to the knowledge graph of clinical information is sufficient to perform population health analytics.

Aspect 21. Any computer-implemented method of aspects 17-20, further comprising generating an electronic health record documentation based at least in part on the mapping

of the knowledge graph of clinical information to the raw data of the clinical encounter.

Aspect 22. The computer-implemented method of aspect 21, further comprising scoring the generated electronic health record documentation to determine a completeness of a patient evaluation for the clinical encounter.

Aspect 23. The computer-implemented method of aspect 22, further comprising adapting the mapping of the knowledge graph of clinical information to the raw data of the clinical encounter to conform to a schema for the electronic health record.

Aspect 24. Any computer-implemented method of aspects 22-23, further comprising adapting the mapping of the knowledge graph of clinical information to the raw data of the clinical encounter to conform to interoperability standards for health information technology systems.

Aspect 25. Any computer-implemented method of aspects 1-24, further comprising determining diagnosis decision support for the clinical encounter based on the knowledge graph of clinical information.

Aspect 26. Any computer-implemented method of aspects 1-25, further comprising determining care plan decision support for the clinical encounter based on the knowledge graph of clinical information.

Aspect 27. Any computer-implemented method of aspects 1-26, further comprising automating procedural terminology for the clinical encounter based on the knowledge graph of clinical information.

Aspect 28. Any computer-implemented method of aspects 1-27, further comprising determining ICD-10 coding for the clinical encounter based on the knowledge graph of clinical information.

Aspect 29. A computing system for generating a knowledge graph of clinical information, the computing system comprising: one or more processors; and a memory storing instructions that, upon execution by the one or more processors, cause the computing system to perform one or more processes including: identifying a clinical encounter associated with a clinical concern; representing the clinical concern as a module of a knowledge graph of clinical information; associating at least one section node with the module, each section node of the at least one section node corresponding to a clinical concept relevant to the clinical concern; associating, for each section node of the at least one section node, at least one topic node with the section node, each topic node of the at least one topic node corresponding to a clinical topic relevant to the corresponding clinical concept; and generating the knowledge graph of clinical information to represent the clinical concern, the relevant clinical concepts, and the relevant clinical topics; wherein associating the at least one section node with the module comprises: determining, for each section node, a concept relevancy between the corresponding clinical concept and the clinical concern; and representing the concept relevancies by the weightings of the connections between the section nodes and the module.

Aspect 30. A non-transitory computer-readable medium storing instructions for generating a knowledge graph of clinical information, the instructions upon execution by one or more processors of a computing system, cause the computing system to perform one or more processes including: identifying a clinical encounter associated with a clinical concern; representing the clinical concern as a module of a knowledge graph of clinical information; associating at least one section node with the module, each section node of the at least one section node corresponding to a clinical concept relevant to the clinical concern; associating, for each section

node of the at least one section node, at least one topic node with the section node, each topic node of the at least one topic node corresponding to a clinical topic relevant to the corresponding clinical concept; and generating the knowledge graph of clinical information to represent the clinical concern, the relevant clinical concepts, and the relevant clinical topics; wherein associating the at least one section node with the module comprises: determining, for each section node, a concept relevancy between the corresponding clinical concept and the clinical concern; and representing the concept relevancies by the weightings of the connections between the section nodes and the module.

The invention can be further defined by one or more of the following examples.

In an Example 1, a computer-implemented method for generating a knowledge graph of clinical information for use as a reference model to semantically represent relevant information related to the practice of medicine, the method comprising: representing a clinical concern as a module of the knowledge graph of clinical information; associating at least one section node with the module, wherein each section node of the at least one section node corresponds to a clinical concept relevant to the clinical concern; associating at least one topic node with the at least one section node, wherein each topic node of the at least one topic node corresponds to a clinical topic relevant to the clinical concept; and outputting the knowledge graph of clinical information to semantically represent the relevant information from a clinical encounter associated with the clinical concern.

In an Example 2, the method of Example 1, wherein the at least one section node corresponds to at least one of the following clinical concepts: history of present illness, review of systems, examination, history, diagnosis, and care plan.

In an Example 3, any method of Examples 1-2, wherein the at least one topic node corresponds to at least one of the following clinical topics: onset, location, pain, alleviating factors, aggravating factors, timing, and reason for visit.

In an Example 4, any method of Examples 1-3, wherein associating the at least one section node with the module further comprises determining a relevancy between the at least one section node and the module.

In an Example 5, the method of Example 4, wherein the relevancy comprises at least one of: specificity, sensitivity, probability, or prevalence.

In an Example 6, any method of Examples 1-5, wherein associating the at least one topic node with the at least one section node further comprises determining a relevancy between the at least one topic node and the at least one sections node.

In an Example 7, the method of Example 6, wherein the relevancy comprises at least one of: specificity, sensitivity, probability, or prevalence.

In an Example 8, any method of Examples 1-7, further comprising associating at least one sub-topic node with the at least one topic node, wherein each sub-topic node of the at least one sub-topic node corresponds to a sub-topic of the clinical topic.

In an Example 9, the method of Example 8, wherein associating the at least one sub-topic node with the at least one topic node further comprises determining a relevancy between the at least one sub-topic node and the at least one topic node.

In an Example 10, the method of Example 9, wherein the relevancy comprises at least one of: specificity, sensitivity, probability, or prevalence.

In an Example 11, any method of Examples 8-10, further comprising associating at least one attribute node with the at least one sub-topic node, wherein each attribute node of the at least one attribute node corresponds to a qualifying attribute for the sub-topic.

In an Example 12, the method of Example 11, wherein associating the at least one attribute node with the at least one sub-topic node further comprises determining a relevancy between the at least one attribute node and the at least one sub-topic node.

In an Example 13, the method of Example 12, wherein the relevancy comprises at least one of: specificity, sensitivity, probability, or prevalence.

In an Example 14, any method of Examples 11-13, wherein the knowledge graph of clinical information comprises a plurality of clinical concerns represented as modules; and wherein the method further comprises associating an attribute node of the at least one attribute node with a sub-topic node associated with another clinical concern of the plurality of clinical concerns.

In an Example 15, the method of Example 14, wherein the attribute node corresponds to at least one of the following attributes: left, right, both, and neither.

In an Example 16, any method of Examples 1-15, wherein the association of the at least one section node with the module and the association of the at least topic node with the at least one section node is based on at least one of the following: recognized standards of care, published practice guidelines, clinical quality metrics, other sources of published clinical information, and general physician knowledge.

In an Example 17, the method of Example 16, further comprising updating the association of the at least one section node with the module and the association of the at least one topic node with the at least one section node when additional information from at least one of the following becomes available: the recognized standards of care, the published practice guidelines, the clinical quality metrics, the other sources of published clinical information, and the general physician knowledge.

In an Example 18, any method of Examples 1-17, further comprising mapping raw data of a clinical encounter to the knowledge graph of clinical information resulting in a state of the knowledge graph pertaining to the clinical encounter.

In an Example 19, the method of Example 18, further comprising using at least one of: machine learning and natural language processing to map the raw data of the clinical encounter to the knowledge graph of the clinical information.

In an Example 20, any method of Examples 18-19, further comprising determining whether the state of the graph resulting from the mapping of the raw data of the clinical encounter to the knowledge graph of clinical information is sufficient to calculate a clinical quality measure.

In an Example 21, any method of Examples 18-20, further comprising determining whether the state of the graph resulting from the mapping of the raw data of the clinical encounter to the knowledge graph of clinical information is sufficient to perform population health analytics.

In an Example 22, any method of Examples 18-21, further comprising generating electronic health record documentation based on the mapping of the knowledge graph of clinical information to the raw data of the clinical encounter.

In an Example 23, the method of Example 22, further comprising scoring the generated electronic health record documentation to determine a completeness of a patient evaluation for the clinical encounter.

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In an Example 24, the method of Example 23, further comprising adapting the mapping of the knowledge graph of clinical information to the raw data of the clinical encounter to conform to a schema for the electronic health record.

In an Example 25, any method of Examples 23-24, further comprising adapting the mapping of the knowledge graph of clinical information to the raw data of the clinical encounter to conform to interoperability standards for health information technology systems.

In an Example 26, any method of Examples 1-25, further comprising determining diagnosis decision support for the clinical encounter based on the knowledge graph of clinical information.

In an Example 27, any method of Examples 1-26, further comprising determining care plan decision support for the clinical encounter based on the knowledge graph of clinical information.

In an Example 28, any method of Examples 1-27, further comprising automating procedural terminology for the clinical encounter based on the knowledge graph of clinical information.

In an Example 29, any method of Examples 1-28, further comprising determining ICD-10 coding for the clinical encounter based on the knowledge graph of clinical information.

Additionally, or alternatively, the methods and systems described herein may be implemented on many different types of processing devices by program code comprising program instructions that are executable by the device processing subsystem. The software program instructions may include source code, object code, machine code, or any other stored data that is operable to cause a processing system to perform the methods and operations described herein. Other implementations may also be used, however, such as firmware or even appropriately designed hardware configured to perform the methods and systems described herein.

The systems' and methods' data (e.g., associations, mappings, data input, data output, intermediate data results, final data results, etc.) may be stored and implemented in one or more different types of computer-implemented data stores, such as different types of storage devices and programming constructs (e.g., RAM, ROM, EEPROM, Flash memory, flat files, databases, programming data structures, programming variables, IF-THEN (or similar type) statement constructs, application programming interface, etc.). It is noted that data structures describe formats for use in organizing and storing data in databases, programs, memory, or other computer-readable media for use by a computer program.

The systems and methods may be provided on many different types of computer-readable media including computer storage mechanisms (e.g., CD-ROM, diskette, RAM, flash memory, computer's hard drive, DVD, etc.) that contain instructions (e.g., software) for use in execution by a processor to perform the methods' operations and implement the systems described herein. The computer components, software modules, functions, data stores and data structures described herein may be connected directly or indirectly to each other in order to allow the flow of data needed for their operations. It is also noted that a module or processor includes a unit of code that performs a software operation and can be implemented for example as a sub-routine unit of code, or as a software function unit of code, or as an object (as in an object-oriented paradigm), or as an applet, or in a computer script language, or as another type of computer code. The software components and/or func-

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tionality may be located on a single computer or distributed across multiple computers depending upon the situation at hand.

The computing system can include client devices and servers. A client device and server are generally remote from each other and typically interact through a communication network. The relationship of client device and server arises by virtue of computer programs running on the respective computers and having a client device-server relationship to each other.

This specification contains many specifics for particular embodiments. Certain features that are described in this specification in the context of separate embodiments can also be implemented in combination in a single embodiment. Conversely, various features that are described in the context of a single embodiment can also be implemented in multiple embodiments separately or in any suitable sub-combination. Moreover, although features may be described above as acting in certain combinations, one or more features from a combination can in some cases be removed from the combination, and a combination may, for example, be directed to a sub-combination or variation of a sub-combination.

Similarly, while operations are depicted in the drawings in a particular order, this should not be understood as requiring that such operations be performed in the particular order shown or in sequential order, or that all illustrated operations be performed, to achieve desirable results. In certain circumstances, multitasking and parallel processing may be advantageous. Moreover, the separation of various system components in the embodiments described above should not be understood as requiring such separation in all embodiments, and it should be understood that the described program components and systems can generally be integrated together in a single software product or packaged into multiple software products.

Although specific embodiments of the present disclosure have been described, it will be understood by those of skill in the art that there are other embodiments that are equivalent to the described embodiments. Accordingly, it is to be understood that the disclosure is not to be limited by the specific illustrated embodiments.

What is claimed is:

1. A computer-implemented method for generating a knowledge graph of clinical information, the method comprising:

identifying a clinical encounter associated with a clinical concern;

representing the clinical concern as a module of a knowledge graph of clinical information;

associating at least one section node with the module, each section node of the at least one section node corresponding to a clinical concept relevant to the clinical concern;

associating, for each section node of the at least one section node, at least one topic node with the section node, each topic node of the at least one topic node corresponding to a clinical topic relevant to the corresponding clinical concept;

generating the knowledge graph of clinical information to represent the clinical concern, the relevant clinical concepts, and the relevant clinical topics;

mapping raw data of a clinical encounter to the knowledge graph of clinical information resulting in a state of the knowledge graph pertaining to the clinical encounter; and

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generating an electronic health record documentation based at least in part on the mapping of the knowledge graph of clinical information to the raw data of the clinical encounter;

wherein associating the at least one section node with the module comprises:

determining, for each section node, a concept relevancy between the corresponding clinical concept and the clinical concern; and

representing the concept relevancies by the weightings of the connections between the section nodes and the module.

2. The computer-implemented method of claim 1, wherein the at least one clinical concept includes: history of present illness, review of systems, examination, history, diagnosis, or care plan.

3. The computer-implemented method of claim 1, wherein the at least one clinical topic includes: onset, location, pain, alleviating factors, aggravating factors, timing, or reason for visit.

4. The computer-implemented method of claim 1, wherein the concept relevancy includes: specificity, sensitivity, probability, or prevalence.

5. The computer-implemented method of claim 1, wherein associating the at least one topic node with the section node comprises:

determining, for each topic node and section node pair, a topic relevancy between the corresponding clinical topic and the corresponding clinical concept; and

representing the topic relevancies by the weightings of the connections between the topic nodes and the section nodes.

6. The computer-implemented method of claim 5, wherein the topic relevancy includes: specificity, sensitivity, probability, or prevalence.

7. The computer-implemented method of claim 1, further comprising associating, for each topic node of the at least one topic node, at least one sub-topic node with the topic node, wherein each sub-topic node of the at least one sub-topic node corresponds to a sub-topic to the corresponding clinical topic.

8. The computer-implemented method of claim 7, wherein associating the at least one sub-topic node with the topic node comprises:

determining, for each sub-topic node and topic node pair, a sub-topic relevancy between the corresponding sub-topic and the corresponding clinical topic; and

representing the sub-topic relevancies by the weightings of the connections between the sub-topic nodes and the topic nodes.

9. The computer-implemented method of claim 8, wherein the sub-topic relevancy includes: specificity, sensitivity, probability, or prevalence.

10. The computer-implemented method of claim 7, further comprising associating, for each sub-topic node of the at least one sub-topic node, at least one attribute node to the sub-topic node, wherein each attribute node of the at least one attribute node corresponds to a qualifying attribute for the sub-topic.

11. The computer-implemented method of claim 10, wherein associating the at least one attribute node with the sub-topic node comprises:

determining, for each attribute node and sub-topic node pair, an attribute relevancy between the corresponding qualifying attribute and the corresponding sub-topic; and

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representing the attribute relevancies by the weightings of the connections between the attribute nodes and the sub-topic nodes.

12. The computer-implemented method of claim 11, wherein the attribute relevancy includes: specificity, sensitivity, probability, or prevalence.

13. The computer-implemented method of claim 10, wherein the knowledge graph of clinical information comprises a plurality of clinical concerns represented as a plurality of modules; and

wherein the method further comprises associating an attribute node of the at least one attribute node with a sub-topic node associated with another clinical concern of the plurality of clinical concerns.

14. The computer-implemented method of claim 13, wherein the attribute node corresponds to at least one of the following attributes: left, right, both, and neither.

15. The computer-implemented method of claim 1, wherein the association of the at least one section node with the module and the association of the at least topic node with the at least one section node is based on at least one of the following: recognized standards of care, published practice guidelines, clinical quality metrics, other sources of published clinical information, and general physician knowledge.

16. The computer-implemented method of claim 15, further comprising updating the association of the at least one section node with the module and the association of the at least one topic node with the at least one section node when additional information from at least one of the following becomes available: the recognized standards of care, the published practice guidelines, the clinical quality metrics, the other sources of published clinical information, and the general physician knowledge.

17. The computer-implemented method of claim 1, further comprising using at least one of: machine learning and natural language processing to map the raw data of the clinical encounter to the knowledge graph of the clinical information.

18. The computer-implemented method of claim 1, further comprising determining whether the state of the graph resulting from the mapping of the raw data of the clinical encounter to the knowledge graph of clinical information is sufficient to calculate a clinical quality measure.

19. The computer-implemented method of claim 1, further comprising determining whether the state of the graph resulting from the mapping of the raw data of the clinical encounter to the knowledge graph of clinical information is sufficient to perform population health analytics.

20. The computer-implemented method of claim 1, further comprising scoring the generated electronic health record documentation to determine a completeness of a patient evaluation for the clinical encounter.

21. The computer-implemented method of claim 20, further comprising adapting the mapping of the knowledge graph of clinical information to the raw data of the clinical encounter to conform to a schema for the electronic health record.

22. The computer-implemented method of claim 20, further comprising adapting the mapping of the knowledge graph of clinical information to the raw data of the clinical encounter to conform to interoperability standards for health information technology systems.

23. The computer-implemented method of claim 1, further comprising determining diagnosis decision support for the clinical encounter based on the knowledge graph of clinical information.

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24. The computer-implemented method of claim 1, further comprising determining care plan decision support for the clinical encounter based on the knowledge graph of clinical information.

25. The computer-implemented method of claim 1, further comprising automating procedural terminology for the clinical encounter based on the knowledge graph of clinical information.

26. The computer-implemented method of claim 1, further comprising determining ICD-10 coding for the clinical encounter based on the knowledge graph of clinical information.

27. A computing system for generating a knowledge graph of clinical information, the computing system comprising:

- one or more processors; and
- a memory storing instructions that, upon execution by the one or more processors, cause the computing system to perform one or more processes including:
 - identifying a clinical encounter associated with a clinical concern;
 - representing the clinical concern as a module of a knowledge graph of clinical information;
 - associating at least one section node with the module, each section node of the at least one section node corresponding to a clinical concept relevant to the clinical concern;
 - associating, for each section node of the at least one section node, at least one topic node with the section node, each topic node of the at least one topic node corresponding to a clinical topic relevant to the corresponding clinical concept;
 - generating the knowledge graph of clinical information to represent the clinical concern, the relevant clinical concepts, and the relevant clinical topics;
 - mapping raw data of a clinical encounter to the knowledge graph of clinical information resulting in a state of the knowledge graph pertaining to the clinical encounter; and
 - generating an electronic health record documentation based at least in part on the mapping of the knowledge graph of clinical information to the raw data of the clinical encounter;
 - wherein associating the at least one section node with the module comprises:

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determining, for each section node, a concept relevancy between the corresponding clinical concept and the clinical concern; and

representing the concept relevancies by the weightings of the connections between the section nodes and the module.

28. A non-transitory computer-readable medium storing instructions for generating a knowledge graph of clinical information, the instructions upon execution by one or more processors of a computing system, cause the computing system to perform one or more processes including:

- identifying a clinical encounter associated with a clinical concern;
- representing the clinical concern as a module of a knowledge graph of clinical information;
- associating at least one section node with the module, each section node of the at least one section node corresponding to a clinical concept relevant to the clinical concern;
- associating, for each section node of the at least one section node, at least one topic node with the section node, each topic node of the at least one topic node corresponding to a clinical topic relevant to the corresponding clinical concept;
- generating the knowledge graph of clinical information to represent the clinical concern, the relevant clinical concepts, and the relevant clinical topics;
- mapping raw data of a clinical encounter to the knowledge graph of clinical information resulting in a state of the knowledge graph pertaining to the clinical encounter; and
- generating an electronic health record documentation based at least in part on the mapping of the knowledge graph of clinical information to the raw data of the clinical encounter;
- wherein associating the at least one section node with the module comprises:
 - determining, for each section node, a concept relevancy between the corresponding clinical concept and the clinical concern; and
 - representing the concept relevancies by the weightings of the connections between the section nodes and the module.

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