

UNITED STATES PATENT AND TRADEMARK OFFICE

BEFORE THE PATENT TRIAL AND APPEAL BOARD

BMJ PUBLISHING GROUP LIMITED,

Petitioner,

v.

EVIDIUM, INC.,

Patent Owner.

Case No. PGR2027-00002

U.S. Patent No. 12,518,883

PETITION FOR POST GRANT REVIEW

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1001	U.S. Patent No. 12,518,883 (“the ’883 patent”)
1002	File History of the ’883 patent
1003	Declaration of Dr. Mark Alan Musen, M.D., Ph.D.
1004	Curriculum Vitae of Dr. Mark Alan Musen, M.D., Ph.D.
1005	U.S. Patent Publication No. 2019/0252074 (“Datla”)
1006	U.S. Patent No. 11,636,949 (“Goldberg”)
1007	U.S. Patent No. 12,248,826 (“Gnanasambandam”)
1008	U.S. Patent Publication No. 2022/0208373 (“Dang”)
1009	U.S. Patent No. 11,194,860 (“Zhong”)
1010	Eryu Xia et al., “Mining Disease-Symptom Relation from Massive Biomedical Literature and Its Application in Severe Disease Diagnosis,” IBM Research (2018) (“Xia”)
1011	U.S. Patent Publication No. 2021/0233658 (“Van Assel”)
1012	U.S. Patent Publication No. 2024/0221952 (“Kim”)
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1016	<i>Evidium, Inc. v. BMJ Publishing Group Limited</i> , Case No. 4:26-cv-05050-AMO (N.D. Cal.) (Dkt. 30) (Sept. 3, 2026) (Amended

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1021	U.S. Patent Publication No. 2019/0026437 (“Syeda-Mahmood”)
1022	U.S. Patent No. 12,512,193 (“Marcjan”)
1023	U.S. Patent Publication No. 2023/0377748 (“Yang”)
1024	U.S. Patent No. 11,488,713 (“Velez”)
1025	U.S. Patent Publication No. 2018/0108443 (“Li”)
1026	U.S. Patent No. 12,014,135 (“Potts”)
1027	U.S. Patent No. 7,260,480 (“Brown”)
1028	Dan McCreary, Knowledge Graphs: The Third Era of Computing, Medium (Mar. 23, 2019) (https://dmccreary.medium.com/knowledge-graphs-the-third-era-of-computing-a8106f343450)
1029	“DocKG: A Knowledge Graph Framework for Health with Doctor-in-the-Loop,” Ming Sheng et al. (“Sheng”)
1030	“Learning a Health Knowledge Graph from Electronic Medical Records,” Maya Rotmensch et al. (July 20, 2017) (“Rotmensch”)

Exhibit No.	Description
1031	“Semantic Health Knowledge Graph: Semantic Integration of Heterogeneous Medical Knowledge and Services,” Longxiang Shi et al. (Feb. 12, 2017) (“Shi”)
1032	“Clinical Decision-Support Systems,” Mark A. Musen et al. (2021) (“Musen Textbook”)
1033	“Artificial Intelligence in Medical Diagnosis,” Peter Szolovits et al. (1988) (“Szolovits”)
1034	“ <i>Internist-I</i> , An Experimental Computer-Based Diagnostic Consultant for General Internal Medicine,” Randolph A. Miller et al. (1982) (“Miller”)
1035	“INTERNIST-1 Properties: Representing Common Sense and Good Medical Practice in a Computerized Medical Knowledge Base,” Fred E. Masarie et al., Computers and Biomedical Research (1985) (“Masarie”)
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1042	History of The BMJ (https://www.bmj.com/about-bmj/history-of-the-bmj)
1043	About – PubMed (https://web.archive.org/web/20200309080055/https://pubmed.ncbi.nlm.nih.gov/about/)
1044	BioPortal API Documentation (https://web.archive.org/web/20140725213752/http://data.bioontology.org/documentation)

CLAIM LISTING

Claim 1	
1pre	A method of providing reasoning capability to integrated medical evidence from medical evidence sources, said method comprising:
1a	receiving, via an application programming interface (API), a medical query from a software application for querying said knowledge graph,
1b	wherein said knowledge graph includes a plurality of nodes, which include a plurality of medical condition nodes, a plurality of finding nodes, and a plurality of investigation nodes,
1c	wherein at least one of said finding nodes in said knowledge graph is traversable to a first medical condition node to indicate that a finding represented by said at least one of said finding nodes is associated with a first medical condition represented by said first medical condition node, and
1d	wherein at least one of said investigation nodes in said knowledge graph is traversable to a second medical condition node to indicate that an investigation represented by said at least one of said investigation nodes is associated with a second medical condition represented by said second medical condition node, and
1e	wherein one or more of said nodes in said knowledge graph are extracted from a plurality of medical evidence sources and are linked to a medical terminology ontology,
1f	wherein said knowledge graph is configured to support reasoning capability by allowing traversal of ancestor-descendant relationships among one or more of said medical condition nodes, said finding nodes, or said investigation nodes, and
1g	wherein said medical terminology ontology includes a Systemized Nomenclature of Medicine Clinical Terms (SNOMED-CT) database, or a Logical Observation Identifiers, Names, and Codes (LOINC) database;
1h	identifying, using said reasoning capability, a set of ancestor-descendant relationships of said knowledge graph that are relevant to said medical query, wherein said reasoning capability including traversing said knowledge graph to identify one or more of said medical condition nodes, said finding nodes, or said investigation

	nodes that are relevant to said medical query; and
1i	outputting, responsive to said medical query, an output to said software application, wherein said output includes data related to one or more of said medical condition nodes, said finding nodes, or said investigation nodes that are relevant to said medical query in order for said software application to generate a medical determination.
Claim 2	
2	A method as recited in claim 1 wherein each of said investigation nodes is linked to a corresponding result node holding a result of said each investigation node, each of said corresponding result nodes being linked to said at least one of said medical condition nodes to which said each investigation node is linked.
Claim 3	
3	A method as recited in claim 2 wherein each of said investigation nodes represents a laboratory test or an examination, and wherein said result node corresponding to said each of said investigation nodes represents a result of said laboratory test or said examination.
Claim 4	
4	A method as recited in claim 1 wherein said finding nodes are diagnostic factor nodes.
Claim 5	
5	A method as recited in claim 1 wherein said software application is an artificial intelligence (AI) application.
Claim 6	
6	A method as recited in claim 1 wherein said medical query includes at least one patient diagnostic factor extracted from an electronic health record (EHR) of a patient, said method further comprising: matching said patient diagnostic factor to one of said finding nodes, wherein said output is a medical condition associated with one of said medical condition nodes to which said one of said finding nodes is linked.
Claim 7	
7	A method as recited in claim 1 wherein said medical query is a clinical state of a patient including at least one likely medical

	condition of said patient and at least one patient diagnostic factor, said method further comprising: matching said patient diagnostic factor to one of said finding nodes, and wherein said output is an unknown diagnostic factor associated with one of said finding nodes that is not yet known to be present or absent in said patient.
Claim 8	
8	A method as recited in claim 1 wherein said each investigation node does not include information specific to a medical condition associated with one of said medical condition nodes to which said each investigation node is linked.
Claim 9	
9	A method as recited in claim 1 wherein each of said investigation nodes is disambiguated across said plurality of medical condition nodes.
Claim 10	
10	A method as recited in claim 1 wherein each of said investigation nodes is independent of said at least one of said medical condition nodes to which said each investigation node is traversable.
Claim 11	
11	A method as recited in claim 1 wherein said knowledge graph further includes for each of said investigation nodes, a data structure different from said each investigation node that is traversable to both said each investigation node and said at least one of said medical condition nodes to which said each investigation node is traversable, said data structure including attributes pertaining to said at least one of said medical condition nodes to which said each investigation node is traversable.
Claim 12	
12	A method as recited in claim 1 wherein at least one of said investigation nodes is traversable to at least two of said medical condition nodes and wherein said at least one of said investigation nodes does not include information specific to medical conditions associated with said at least two of said medical condition nodes.
Claim 13	
13	A method as recited in claim 1 wherein said knowledge graph

	further includes on a path between each medical condition node and each of said investigation nodes to which said each medical condition node is traversable, a ranking value indicating how likely it is that an investigation represented by said each investigation node is indicative of a medical condition represented by said each medical condition node.
Claim 14	
14	A method as recited in claim 1 wherein said knowledge graph further includes on a path between each medical condition node and each of said investigation nodes to which said each medical condition node is traversable, at least one condition-dependent attribute of a medical condition represented by said each medical condition node.
Claim 15	
15	A method as recited in claim 1 wherein said software application is a natural language processing (NLP) engine that receives verbatim text and produces said medical query that includes a patient diagnostic factor or a patient medical condition, and wherein said matching a portion includes matching said patient diagnostic factor to said at least one of said finding nodes or matching said patient medical condition to said at least one of said medical condition nodes to produce said output.
Claim 16	
16	A method as recited in claim 15 wherein said NLP engine is initialized with at least one of said plurality of finding nodes from said knowledge graph in order to facilitate said matching.
Claim 17	
17	A method as recited in claim 1 wherein said software application causes said output to be displayed on a computer to a user.
Claim 18	
18	A method as recited in claim 1 wherein said output is output to said software application in a data structure suitable for further processing.
Claim 19	
19	A method as recited in claim 1 further comprising: in response to

	said output, receiving at said knowledge graph a new patient diagnostic factor known to be present or absent in said patient; and outputting, from said knowledge graph and responsive to said new patient diagnostic factor, a new output.
Claim 20	
20	A method as recited in claim 1 further comprising: matching a portion of said medical query to at least one of said medical condition nodes or to at least one of said finding nodes to produce said output.
Claim 21	
21	A method as recited in claim 1 wherein said knowledge graph includes more than twenty thousand nodes.
Claim 22	
22	A method as recited in claim 1 wherein said knowledge graph includes more than one hundred thousand nodes.
Claim 23	
23pre	A system for providing reasoning capability to integrated medical evidence from medical evidence sources, the system comprising:
23a	a database that stores a knowledge graph including a plurality of nodes, which include a plurality of medical condition nodes, a plurality of finding nodes, and a plurality of investigation nodes,
23b	wherein at least one of said finding nodes in said knowledge graph is traversable to a first medical condition node to indicate that a finding represented by said at least one of said finding nodes is associated with a first medical condition represented by said first medical condition node,
23c	wherein at least one of said investigation nodes in said knowledge graph is traversable to a second medical condition node to indicate that an investigation represented by said at least one of said investigation nodes is associated with a second medical condition represented by said second medical condition node,
23d	wherein one or more of said nodes in said knowledge graph are extracted from a plurality of medical evidence sources and are linked to a medical terminology ontology,
23e	wherein said knowledge graph is configured to support reasoning

	capability by allowing traversal of ancestor-descendant relationships among one or more of said medical condition nodes, said finding nodes, or said investigation nodes, and
23f	wherein said medical terminology ontology includes a Systemized Nomenclature of Medicine—Clinical Terms (SNOMED-CT) database, or a Logical Observation Identifiers, Names, and Codes (LOINC) database;
23g	a computer system comprising one or more processors and memory that stores instructions, wherein the instructions, when executed by the one or more processors, cause the one or more processors to:
23h	receive, via an application programming interface (API), a medical query from a software application for querying said knowledge graph;
23i	identify, using said reasoning capability, a set of ancestor-descendant relationships of said knowledge graph that are relevant to said medical query, wherein said reasoning capability including traversing said knowledge graph to identify one or more of said medical condition nodes, said finding nodes, or said investigation nodes that are relevant to said medical query; and
23j	output, responsive to said medical query, an output to said software application, wherein said output includes data related to one or more of said medical condition nodes, said finding nodes, or said investigation nodes that are relevant to said medical query in order for said software application to generate a medical determination.
Claim 24	
24	A system as recited in claim 23, wherein each of said investigation nodes is linked to a corresponding result node holding a result of said each investigation node, each of said corresponding result nodes being linked to said at least one of said medical condition nodes to which said each investigation node is linked.
Claim 25	
25	A system as recited in claim 23, wherein said finding nodes are diagnostic factor nodes.
Claim 26	
26	A system as recited in claim 23, wherein said each investigation node does not include information specific to a medical condition

	associated with one of said medical condition nodes to which said each investigation node is traversable.
Claim 27	
27	A system as recited in claim 23, wherein each of said investigation nodes is disambiguated across said plurality of medical condition nodes.
Claim 28	
28	A system as recited in claim 23, wherein each of said investigation nodes is independent of said at least one of said medical condition nodes to which said each investigation node is traversable.
Claim 29	
29	A system as recited in claim 23, wherein said knowledge graph further includes for each of said investigation nodes, a data structure different from said each investigation node that is traversable to both said each investigation node and said at least one of said medical condition nodes to which said each investigation node is traversable, said data structure including attributes pertaining to said at least one of said medical condition nodes to which said each investigation node is traversable.
Claim 30	
30	A system as recited in claim 23, wherein at least one of said investigation nodes is traversable to at least two of said medical condition nodes and wherein said at least one of said investigation nodes does not include information specific to medical conditions associated with said at least two of said medical condition nodes.
Claim 31	
31	A system as recited in claim 23, wherein said knowledge graph further includes on a path between each medical condition node and each of said investigation nodes to which said each medical condition node is traversable, a ranking value indicating how likely it is that an investigation represented by said each investigation node is indicative of a medical condition represented by said each medical condition node.
Claim 32	
32	A system as recited in claim 23, wherein said knowledge graph

	further includes on a path between each medical condition node and each of said investigation nodes to which said each medical condition node is traversable, at least one condition-dependent attribute of a medical condition represented by said each medical condition node.
Claim 33	
33	A system as recited in claim 23 wherein said knowledge graph includes more than twenty thousand nodes.
Claim 34	
34	A system as recited in claim 23 wherein said knowledge graph includes more than one hundred thousand nodes.

I. INTRODUCTION

Petitioner BMJ Publishing Group Limited (“Petitioner” or “BMJ”) requests post grant review of claims 1-34 (“challenged claims”) of U.S. Patent No. 12,518,883 (“’883 patent”). The ’883 patent claims a knowledge graph that stores condition, finding, and investigation nodes drawn from medical literature and linked to a medical ontology; traverses the ontology’s ancestor-descendant hierarchy in response to a query received through an application programming interface (“API”); and returns the relevant nodes to a software application. Each of these features was well known in the art prior to 2022.

The specification concedes that many of the building blocks of the claims already existed. For example, it acknowledges that medical publishers were already assembling published evidence into diagnostic reference content, and it draws the claimed knowledge graph’s content from those same existing medical evidence sources. The specification further concedes that the system links to pre-existing ontologies such as SNOMED-CT and LOINC, stores information in any of a variety of conventional databases, and makes information available to software applications through standard healthcare APIs. Even the claimed “reasoning capability” is simply the familiar practice of moving up or down an ontology’s hierarchy, for example inferring that a patient with “acute fever” also has “fever,” which is how clinical terminologies had been used for decades.

The prior art taught every element. Goldberg discloses “a healthcare knowledge graph database for storing a medical hybrid knowledge graph” built from books, articles, and publications and integrated with SNOMED and LOINC, with disease, symptom, and laboratory-test nodes and a diagnostic algorithm that selects pathways through SNOMED “is-a” relations to generate differential diagnoses. EX1006, Abstract, 5:42-62, 6:10-44, 15:60-16:56, FIGS. 1, 6-7, 9-10. Gnanasambandam publishes APIs that “use artificial intelligence to perform analytics based on a knowledge graph” for client software applications. EX1007, 100:24-40, claim 1. Dang confirms the graph topology and query-time hyponymy reasoning, and Datla supplies the natural-language front end recited in claims 15-16. EX1008 ¶¶[0027]-[0031], [0047]-[0051]; EX1005 ¶¶[0006]-[0008], [0052], [0055]. Neither Gnanasambandam (EX1007) nor Dang appears among the references cited on the face of the ’883 patent. EX1001, code (56). Grounds 1 and 2 thus establish that claims 1-34 would have been obvious. EX1003 ¶¶126-404.

The claims are also ineligible under 35 U.S.C. § 101. The Examiner rejected every claim as reciting mental processes performed with generic components, and withdrew that rejection only because “a human cannot implement a software application in his or her mind in order to access a knowledge graph via an API.” EX1002, 16-17, 88-90. That rationale is legally erroneous: a generic API does not

transform the abstract idea of collecting, organizing, reasoning over, and reporting medical information into patent-eligible subject matter. *Infra* §XI.

Because it is more likely than not that at least one challenged claim is unpatentable (*see* 35 U.S.C. § 324(a)), the Board should institute review and cancel claims 1-34.

II. COMPLIANCE WITH PGR REQUIREMENTS

A. Standing

Petitioner certifies that the '883 patent is an AIA patent and is available for PGR. Petitioner is not barred or estopped from requesting a PGR on the challenged claims on the grounds below. Petitioner has not filed a civil action challenging the validity of any claim of the '883 patent.

This petition is timely because it is being filed within one year of service of Evidium's complaint alleging infringement of the '883 patent and within 9 months of the '883 patent's January 6, 2026, issue date. 35 U.S.C. § 321(c); 37 C.F.R. § 42.202(a).

B. Mandatory Notices

1. Real Party-in-Interest

Petitioner BMJ Publishing Group Limited, which is wholly owned by the British Medical Association, is the real party-in-interest. No other party had access to or control over the Petition, and no other party funded or participated in preparation of this Petition.

2. Related Proceedings

The '883 patent is related to the following U.S. Patents: 11,869,674, 12,518,882, 12,300,392, 12,525,362, 12,542,217, 12,640,274, and 12,725,716 and pending U.S. Patent Application No. 19/722,113.

The '883 patent and certain related patents are at issue in *Evidium, Inc. v. BMJ Publishing Group Limited*, Case No. 4:26-cv-05050-AMO (N.D. Cal.) (“the NDCA Action”). The complaint (EX1015) was filed on May 28, 2026, and served on June 8, 2026 (EX1018).

3. Counsel and Service Information

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III. PAYMENT OF FEES

Pursuant to 37 C.F.R. § 42.15(b), the required fee is being submitted herewith. The Office is authorized to charge any deficiency, or credit overpayment, to Deposit Account No. 50-4181. Any additional fees due in connection with this Petition may be charged to the foregoing account.

IV. IDENTIFICATION OF CHALLENGED CLAIMS

Ground 1: Claims 1-14 and 17-34 are unpatentable as obvious over Goldberg, Gnanasambandam, and Dang.

Ground 2: Claims 15-16 are unpatentable as obvious over Goldberg, Gnanasambandam, Dang, and Datla.

Ground 3: Claims 1-34 are unpatentable under 35 U.S.C. § 101.

Petitioner's challenges are supported by the declaration and testimony of Mark A. Musen, M.D., Ph.D. EX1003 ¶¶125-404.

V. TECHNICAL BACKGROUND

The '883 patent purports to transform unstructured medical evidence into a computational knowledge graph of medical condition, finding, and investigation nodes. But every technology the claims recite—standardized medical ontologies, medical knowledge graphs, clinical decision support systems, API-based access to medical knowledge, and hierarchical reasoning—was well known before the '883 patent's priority date. EX1003 ¶57.

A. Medical Ontologies and Terminologies

A medical ontology is a structured, formal representation of medical knowledge that defines concepts such as conditions, findings, and investigations, and the relationships among them. EX1003 ¶58. Ontologies had been used for decades in clinical information systems, electronic health records ("EHRs"), and

clinical decision support applications. *Id.*

The Systematized Nomenclature of Medicine—Clinical Terms (“SNOMED-CT”) is among the most comprehensive and widely used clinical terminologies in the world. EX1003 ¶¶59-60. By 2022, SNOMED-CT contained hundreds of thousands of concepts organized in hierarchies connected by “is-a” and other relationships (e.g., Bacterial Pneumonia is-a Infective Pneumonia is-a Pneumonia). EX1003 ¶¶61-64; EX1006, 1:54-56, FIG. 6. That organization enables traversal of ancestor-descendant relationships among concepts. EX1003 ¶63. The Logical Observation Identifiers, Names, and Codes (“LOINC”) is a standard terminology for laboratory tests, clinical measurements, and related observations that, by 2022, included codes for tens of thousands of observations. EX1003 ¶¶66-67. Many other terminologies, including ICD, RxNorm, the Gene Ontology, and MeSH, were also in wide use, and the NCBO’s BioPortal made hundreds of biomedical ontologies publicly available and searchable beginning in the mid-2000s. EX1003 ¶¶69-71.

The ’883 patent itself acknowledges that SNOMED-CT and LOINC are pre-existing ontologies. EX1001, 4:12-37, 5:4-19; EX1003 ¶¶65, 68.

B. Healthcare Knowledge Graphs

A knowledge graph is a structured representation of entities (“nodes”) and the relationships among them (“edges”) that enables efficient traversal, querying, and reasoning. EX1003 ¶74. In healthcare, knowledge graphs were used to represent

medical conditions, findings (e.g., symptoms, signs, and test results), investigations (e.g., tests and procedures), medications, and the relationships among them. EX1003 ¶¶75-77; EX1006, 6:10-30; EX1011 ¶[0115]; EX1008, FIGS. 1A-1B.

Practitioners routinely built medical knowledge graphs from multiple evidence sources, including peer-reviewed literature (e.g., The BMJ, JAMA, The Lancet, and NEJM, indexed through resources such as PubMed), clinical guidelines, SNOMED-CT and LOINC, and EHRs. EX1003 ¶¶72-73, 80. Graphs were constructed manually by subject-matter experts, automatically using NLP and machine learning, or through human-in-the-loop approaches combining the two. EX1003 ¶¶80-82; EX1006, 6:5-30. By 2022, constructing and using medical knowledge graphs to integrate clinical evidence, support clinical reasoning, and enable computerized decision support was well known and widely practiced. EX1003 ¶83.

C. Clinical Decision Support Systems

Clinical decision support systems (“CDSS”) are computer-based tools that provide clinicians and other healthcare stakeholders with person-specific, intelligently filtered, and timely information to enhance health-related decisions. EX1003 ¶84. CDSS have been in use since the 1970s; early examples include MYCIN and INTERNIST-1, which performed diagnostic decision support. *Id.* INTERNIST-1 modeled conditions and findings using data structures, including

separate representation of conditions and findings, association of individual findings with multiple conditions, and patient characteristics (demographics) that constrain when a condition can occur. *Id.* ¶85. By the priority date, CDSS routinely leveraged structured knowledge bases—including knowledge graphs—to support diagnostic reasoning, treatment recommendations, and other clinical decisions. *Id.* ¶86.

D. APIs

An application programming interface (“API”) is a set of protocols, routines, and tools that allow software applications to communicate with one another. EX1003 ¶87. Using APIs to access medical knowledge bases and ontologies was well established before the priority date. *Id.*; EX1007, 100:24-34. For example, BioPortal has provided RESTful APIs since 2006 that allow external applications to search, browse, and query hundreds of biomedical ontologies; the National Library of Medicine’s Unified Medical Language System (“UMLS”) has long offered API-based terminology services; and HL7’s FHIR standard includes terminology-service APIs. EX1003 ¶88. In such systems, an API receives a medical query from a software application and returns the output to that application. EX1003 ¶¶88-89.

E. Reasoning over Medical Hierarchies

Ontologies like SNOMED-CT are organized as hierarchies in which each concept may have multiple parents and children that support traversal of ancestor–descendant relationships. EX1003 ¶¶90-91. A query about a specific disease can be

generalized to its ancestors to find broadly relevant findings or specialized to its descendants to find more specific diagnostic information. EX1003 ¶90. Reasoning systems had long exploited these relationships to generalize and specialize clinical queries, identify relevant concepts, and support clinical decision-making. *Id.* ¶91.

VI. THE '883 PATENT

A. AIA Status

The earliest alleged priority date of the '883 patent is April 15, 2022. EX1001, code (60). The '883 patent was examined as an AIA patent. EX1002, 88.

B. Level of Skill in the Art

A person of ordinary skill in the art (“POSITA”) would have had at least a master’s degree in biomedical informatics, computer science, health informatics, or a closely related field and at least two years of experience working with medical knowledge representation systems, biomedical ontologies, knowledge graphs, or clinical decision support systems. A POSITA would also have had a good working knowledge of biomedical ontologies and terminologies, knowledge-graph construction and querying, clinical decision-support methodologies, graph-based reasoning, APIs for accessing structured medical knowledge, and integrating medical evidence from multiple sources. Additional education can compensate for less professional experience, and vice versa. EX1003 ¶¶28-31.

C. Overview of the '883 Patent

The '883 patent describes a “computational evidence platform” that extracts clinical concepts from medical evidence sources and stores them in a graph database of interlinked elements—conditions, diagnostic factors, risk factors, and investigations—that software applications can query. EX1001, Abstract, 2:43-62; EX1003 ¶93. The specification concedes that the underlying task was not new: publishers “such as DynaMed, BMJ, UpToDate” already assembled published evidence into diagnostic reference content, albeit through “human-centric” activity. EX1001, 1:59-65; EX1003 ¶94. The purported advance is simply rendering that evidence in “computational” form. EX1003 ¶¶93-94.

The claimed “knowledge graph” is graph database 50, which may be “[a]ny of a wide variety of” databases, including a relational database, an object store, or an off-the-shelf JanusGraph graph database. EX1001, 8:10-22. Finding nodes are called “elemental diagnostic factors” (EDFs), which are signs and symptoms a physician can observe or a patient can describe; investigation nodes are “elemental diagnostic investigations” (EDIs), which are laboratory tests or specialist examinations. EX1001, 8:4-9, 9:21-28, 9:61-10:10, 11:65-12:8; EX1003 ¶95. As FIG. 4A shows, condition nodes link to EDFs through “factor groups” and to EDIs through “investigation groups” and “EDI Result” nodes. EX1001, FIG. 4A, 18:28-19:24; EX1003 ¶96. EDFs and EDIs “do not include information specific to their

associated conditions,” so each can be shared across conditions, while condition-dependent attributes such as rankings and test results reside in the intermediate group and result nodes. EX1001, Abstract, 21:18-21, 22:12-21; EX1003 ¶¶215-216, 279. The specification adds that these elements “need not necessarily be implemented ... as nodes.” EX1001, 17:64-18:9; EX1003 ¶274.

The graph’s content is drawn from well-known evidence sources, including BMJ Best Practice, using conventional NLP techniques. EX1001, 7:4-22, 7:56-8:9; EX1003 ¶¶97-98. The platform maps that content to pre-existing ontologies like SNOMED-CT, LOINC, and RxNORM. EX1001, 5:13-19; EX1003 ¶99. A “reasoning service” then walks the ontology’s ancestor–descendant chains; for example, it infers that a patient with “acute fever” also has “fever,” or that a CBC with differential is a parent of a CBC. EX1001, 8:38-58, 23:61-24:15; EX1003 ¶100.

Clinicians access the platform through a “diagnostic glass” application that communicates with the backend through APIs the specification identifies as FHIR, USCDI, CDS Hooks, and vendor-specific APIs. EX1001, 5:52-54, 6:4-8, 6:13-26; EX1003 ¶101. The output is “the likely, ranked conditions of the patient, along with for each, unknown factors that should be queried and investigations that should be performed.” EX1001, 9:5-17; EX1003 ¶103.

D. Prosecution History

The '883 patent was filed as U.S. Patent Application No. 19/050,872 on February 11, 2025, with a Track One request. EX1002, 122. In the only Office action, all claims were rejected under § 101 and § 102(a)(2). EX1002, 86-105.

Under § 101, the Examiner found that the claims recited “observation, evaluation, and judgement that can be practically performed by a human,” and that, apart from a generic “application programming interface (API)” and “a computer system comprising one or more processors and memory,” nothing precluded performing the steps mentally. EX1002, 88-89. The Examiner further found that receiving a query via an API and outputting results to a software application were “insignificant extra-solution activity” and “well-understood, routine, and conventional.” EX1002, 89-90; EX1003 ¶108. Under § 102, the Examiner found the claims anticipated by U.S. Patent Publication No. 2023/0115939 (“Gnanasambandam '939”).¹ EX1002, 95-103.

In response, the applicant amended the claims to require that nodes be “extracted from a plurality of medical evidence sources and ... linked to a medical terminology ontology”; that the graph support “traversal of ancestor-descendant

¹ This “Gnanasambandam” reference is different from EX1007, which was not considered.

relationships”; and that the output enable the software application “to generate a medical determination.” EX1002, 50-55. For § 102, the applicant argued that Gnanasambandam ’939 disclosed graphs covering only a single medical condition, did not disclose SNOMED-CT or LOINC, and did not disclose ancestor-descendant traversal. EX1002, 59-61; EX1003 ¶113. For the § 101 rejection, the applicant argued that “a human cannot implement a software application in his or her mind in order to access a knowledge graph via an API.” EX1002, 58-59.

The § 101 rejection was withdrawn solely because the API is allegedly “a software construct that a human cannot practically perform in his or her mind ... in order to access a knowledge graph.” EX1002, 16-17. The § 102 rejection was withdrawn because the prior art of record did not teach the combination of an API-based query, ancestor-descendant reasoning, and output to a software application. *Id.*, 17.

As set forth below, each element the applicant relied on for allowance is disclosed in the prior art. Goldberg discloses a knowledge graph spanning multiple diseases that integrates SNOMED and LOINC and includes “is-a” hierarchies, and Gnanasambandam discloses published APIs for knowledge-graph analytics. EX1003 ¶118; *infra* §IX. The § 101 allowance rested on the API alone, which does not confer eligibility. *Infra* §XI.B.

VII. CLAIM CONSTRUCTION

Claims are given their plain and ordinary meaning as understood by a person of skill in the art. 37 C.F.R. § 42.200(b). Petitioner is unaware of any prior claim construction determination related to the '883 patent. Because the challenged claims are unpatentable under any interpretation consistent with their plain and ordinary meaning, the Board need not expressly construe any claim term.

VIII. SUMMARY OF THE ASSERTED REFERENCES

The Examiner never applied any reference relied on in this Petition; the only prior-art rejections relied on a different Gnanasambandam reference. EX1002, 95-103. Although Datla and Goldberg are cited on the face of the '883 patent, the Examiner did not apply either reference in any rejection. EX1001, code (56). Gnanasambandam and Dang were not cited or considered during prosecution. EX1001, code (56).

A. Goldberg

Goldberg is a U.S. patent that issued on April 25, 2023, from an application filed on August 12, 2019. EX1006, codes (22), (45). Goldberg qualifies as prior art to the '883 patent at least under 35 U.S.C. § 102(a)(2).

Goldberg discloses a hybrid knowledge graph and CDSS that integrates medical knowledge from books, articles, publications, and personal knowledge with ontology-based graphs, including SNOMED and LOINC. EX1006, 5:47-62; 6:5-44.

Goldberg's Patient Management App receives patient history, symptoms, signs, laboratory results, and other clinical features, and its inference engine uses probabilistic associations and graph pathways to generate diagnoses and recommend next steps. EX1006, Abstract, 7:25-50; 8:14-40. Goldberg further describes a database, a user interface, and pathways connecting disease, symptom, complication, laboratory-test, and treatment nodes. EX1006, 12:44-54, 15:40-65; EX1003 ¶120.

Goldberg is analogous to the '883 patent at least because it is in the same field of endeavor, systems and methods for automating access to medical data. EX1006, 1:17-20; EX1001, 1:24-28.

B. Gnanasambandam

Gnanasambandam is a U.S. patent that issued on March 11, 2025, from an application filed on April 29, 2022, as a national-phase application of a Patent Cooperation Treaty application having an international filing date of October 30, 2020. EX1007, codes (22), (45), (86). Gnanasambandam qualifies as prior art to the '883 patent at least under 35 U.S.C. § 102(a)(2). *See* 35 U.S.C. § 363.

Gnanasambandam discloses a healthcare cognitive-intelligence platform that uses artificial intelligence to perform analytics based on a medical knowledge graph containing ontological data for medical conditions. EX1007, 1:32-42; claim 1. The platform publishes APIs for use by client devices and software applications, including APIs that provide medical analytics and diagnosis-related outputs.

EX1007, 100:24-40; 101:12-37; 102:22-24, 101:66-102:5, 62:13-15. Gnanasambandam's platform can process evidence-based guidelines, physician research, patient notes in EMRs, and other inputs, and can perform successive rounds of analysis through an application-accessible interface. EX1007, 8:24-39; 30:40-33:30; EX1003 ¶121.

Gnanasambandam is analogous to the '883 patent at least because it is in the same field of endeavor, systems and methods for automating access to medical data. EX1007, 1:28-31; EX1001, 1:24-28.

C. Dang

Dang is a U.S. patent application that published on June 30, 2022, from an application filed on December 31, 2020. EX1008, codes (22), (43). Dang qualifies as prior art to the '883 patent at least under 35 U.S.C. § 102(a)(2).

Dang discloses a graph-based clinical diagnosis system with a multi-tier knowledge graph. FIG. 1A illustrates distinct node types such as Disease, Symptom, Sign, Lab Test and Check, and Observation Item. EX1008 ¶[0027]; FIG. 1A. Dang's FIG. 1B illustrates an intermediate feature tier and disease nodes connected by probabilistic edges. EX1008 ¶¶[0027]-[0031]; FIG. 1B; EX1003 ¶122.

Dang detects factual nodes from patient complaint records, reasons through hyponymy relationships, infers evidential and feature nodes, identifies possible

diseases, and can select a next inquiry using a measure of diagnostic discrimination.

EX1008 ¶¶[0047]-[0059]; FIGS. 5-7; EX1003 ¶122.

Dang is analogous to the '883 patent at least because it is in the same field of endeavor, systems and methods for automating access to medical data. EX1008 ¶[0001]; EX1001, 1:24-28.

D. Datla

Datla is a U.S. patent application that published on August 15, 2019, from an application filed on April 15, 2019, as a national-phase application of a Patent Cooperation Treaty application having an international filing date of October 24, 2017. EX1005, codes (22), (43), (86). Datla qualifies as prior art to the '883 patent at least under 35 U.S.C. § 102(a)(1).

Datla discloses a natural-language clinical-query system. Its NLP engine receives natural-language input, extracts patient symptoms and demographic information, and queries a knowledge graph whose symptom nodes connect to diseases and medical conditions. EX1005, Abstract; ¶¶[0006]-[0008], [0028], [0036], [0052], [0055]-[0057]; claim 1. The system produces a diagnosis graph and a ranked list of medical conditions, diagnoses, treatments, or tests. *Id.*; EX1003 ¶¶123-124.

Datla is analogous to the '883 patent at least because it is in the same field of endeavor, systems and methods for automating access to medical data. EX1005 ¶[0001]; EX1001, 1:24-28.

IX. Ground 1: Claims 1-14 and 17-34 are Obvious Over Goldberg, Gnanasambandam, and Dang

Claims 1-14 and 17-34 would have been obvious over Goldberg, Gnanasambandam, and Dang. EX1003 ¶¶126-383. In the combination, Goldberg supplies the integrated evidence graph, the medical-condition, finding, and investigation relationships, the ontology-linked hierarchy, and the diagnostic pathway search. Gnanasambandam supplies the published API layer. Dang supplies additional support to the extent Goldberg is found not to disclose a particular graph-topology or reasoning feature. EX1003 ¶¶131-213.

A. Motivation to Combine

A POSITA would have been motivated to combine Goldberg, Gnanasambandam, and Dang because the references address the same problem—using structured medical knowledge to support clinical diagnosis—and their teachings are complementary. EX1003 ¶127. Goldberg supplies the hybrid evidence graph, its disease, symptom, complication, laboratory-test, and treatment relationships, and the diagnostic inference engine. EX1006, Abstract, 5:51-62; 6:10-34; 7:14-35; EX1003 ¶127. Gnanasambandam supplies a conventional deployment layer: published APIs that allow external software applications to invoke AI

analytics over a medical knowledge graph and receive the results. EX1007, 100:24-40, 101:12-37; EX1003 ¶¶127-128. Dang supplies an expressly graph-based implementation with distinct factual, intermediate, and disease node tiers, directional connections, hyponymy reasoning, and a next-inquiry process. EX1008 ¶¶[0027]-[0031], [0047]-[0059]; FIGS. 1A, 1B, 5-7; EX1003 ¶129.

The combination would have been a straightforward application of known techniques to a system ready for improvement. EX1003 ¶130. Goldberg already separates a client-facing application from a cloud-based inference engine and knowledge base; the unnamed network interface between those components is the natural location for Gnanasambandam's published API. EX1006, FIG. 2, 7:14-18, 8:9-11; EX1003 ¶¶128, 137-146. The API would transport Goldberg's existing patient-query inputs and diagnostic outputs without changing the underlying graph or inference algorithm. EX1003 ¶¶128, 146.

Dang's graph topology likewise would have been a predictable implementation choice. EX1003 ¶129. Goldberg expressly identifies laboratory tests as a distinct node set and uses pathways connecting those nodes to diseases. EX1006, 16:60-17:3, 17:31-34; FIGS. 1, 4. Dang illustrates how factual test nodes can be represented as distinct nodes connected through an intermediate feature tier to disease nodes, with probabilities on the connections. EX1008 ¶¶[0027]-[0031], FIG.

1B. Using Dang's explicit topology would improve traversal and clarify how the diagnostic algorithm processes tests. EX1003 ¶¶129, 160-162.

The proposed combination also has a reasonable expectation of success. Each reference describes an implemented healthcare knowledge system using ordinary software, databases, graph relationships, and diagnostic analytics. EX1003 ¶130. The combination uses each reference for its known purpose: Goldberg for evidence integration and diagnostic reasoning, Gnanasambandam for API-based access, and Dang for graph organization and query-time reasoning. EX1003 ¶¶127-129. The result would have been a predictable clinical decision-support system. EX1003 ¶130.

B. Independent Claim 1

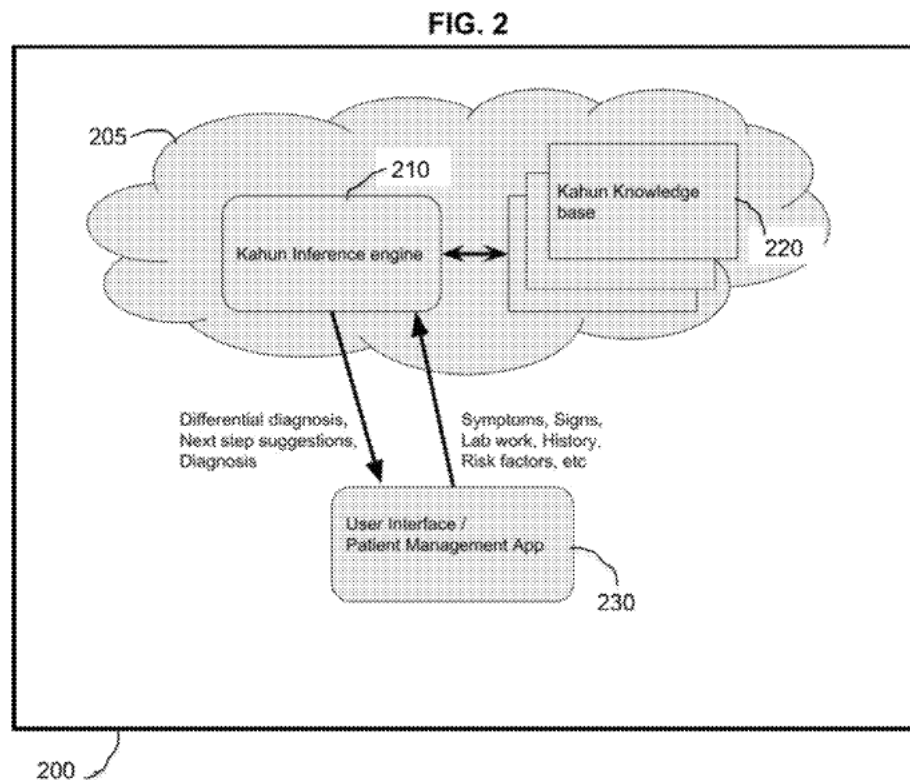
1. Element [1pre]: A method of providing reasoning capability to integrated medical evidence from medical evidence sources, said method comprising

To the extent the preamble is limiting, Goldberg discloses a method of providing reasoning capability to integrated medical evidence from medical evidence sources. EX1003 ¶133. Goldberg describes “a healthcare knowledge graph database for storing a medical hybrid knowledge graph” and “a data processing engine running a diagnostic algorithm” that can “select one or more pathways on the knowledge graph to generate[] one or more differential diagnoses.” EX1006, Abstract; EX1003 ¶133. Goldberg translates knowledge “from multiple sources

(e.g., books, articles, publications, personal knowledge etc.)” into a knowledge graph. *Id.*, 5:47-62, 6:20-40; EX1003 ¶133. The knowledge graph supplies the integrated evidence and the diagnostic algorithm supplies the reasoning capability by selecting pathways and generating differential diagnoses. EX1003 ¶133.

2. Element [1a]: “receiving, via an application programming interface (API), a medical query from a software application for querying said knowledge graph”

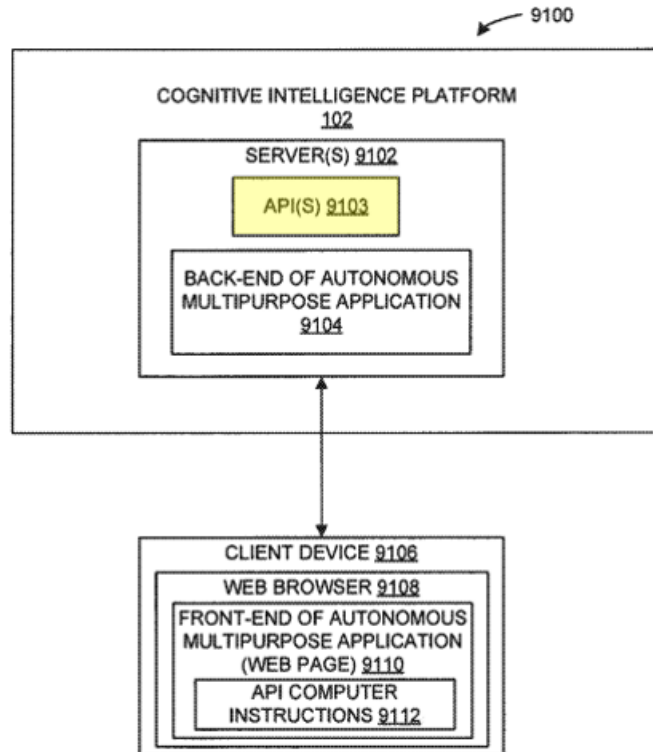
Goldberg’s platform 200 includes “a cloud-based inference engine 210, communicatively coupled to a knowledge base 220, and a patient management App. 230.” EX1006, 7:14-18, FIG. 2.



EX1006 FIG. 2

The App 230 receives “a list of given history, symptoms, signs and other clinical features” and “generates a list of suspected diseases and complications.” EX1006, 7:25-30; EX1003 ¶143. Goldberg further states that the application may be implemented with front-end and server-side software and is “an interface for query-based interaction with the knowledge base.” EX1006, 8:9-11, 8:59-62; EX1003 ¶143. Its example queries ask, “How do CROHN’s and CELLIAC [sic] compare” and “what are all the diseases which could present with a ‘Failure to Thrive.’” EX1006, 9:1-20; EX1003 ¶143. Thus, App 230 is the software application, the patient data or comparison question is the medical query, and knowledge base 220 is the queried knowledge graph. EX1003 ¶¶137, 143. Goldberg does not, however, refer to an “API.” EX1003 ¶138. As discussed above, APIs for knowledge graph access were well-known in the art. *Supra* §V.D; EX1003 ¶138.

Gnanasambandam supplies an express API and discloses “[a]pplication back-end component 9104 is configured to publish one or more APIs 9103” that “may use artificial intelligence to perform analytics based on a knowledge graph pertaining to ontological data of a medical condition.” EX1007, 100:24-34; claim 1; FIG. 91; EX1003 ¶¶139-140.



EX1007 FIG. 91 (annotated)

The back end provides “computer instructions 9112 of the one or more APIs 9103” to client device 9106, whose front end may be “an Internet-enabled application executing on client device 9106.” EX1007, 100:34-40, 100:2-4. The client subscribes to and invokes the APIs, including through HTTP messages. EX1007, 100:28-34, 101:3-24, 102:37-46, FIG. 92; EX1003 ¶141.

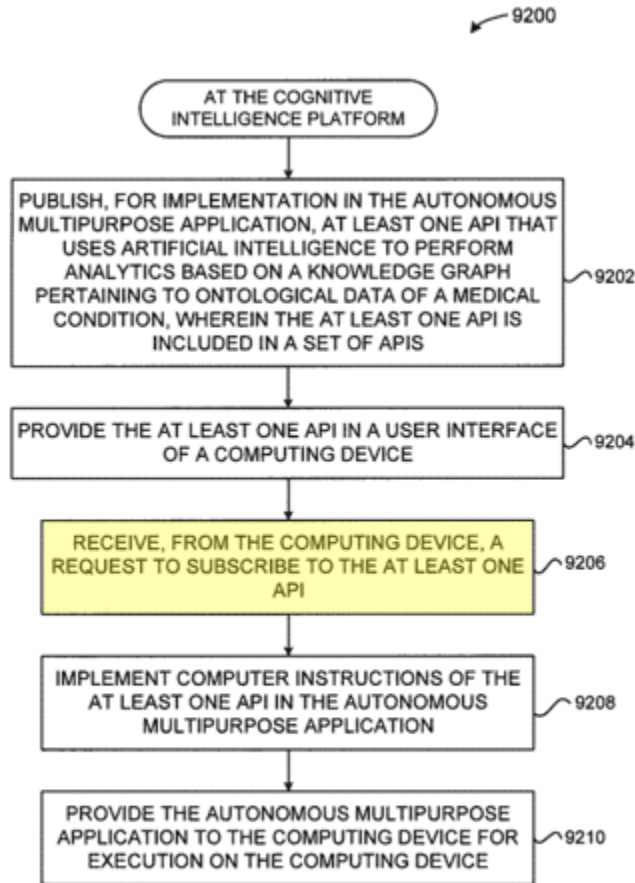


FIG. 92

EX1007 FIG. 92 (annotated)

Gnanasambandam also identifies APIs as an interoperability layer for a cognitive-intelligence platform in healthcare. EX1007, 101:55-67, 102:4-21; EX1003 ¶144.

The combined four-step flow is straightforward: Goldberg's App 230 collects the patient inputs or comparison question; the App sends that request through Gnanasambandam's published API to the server side; Goldberg's inference engine 210 runs the diagnostic algorithm over knowledge base 220; and the API returns the differential, next step, or comparison to the App. EX1003 ¶145. A POSITA would

have used Gnanasambandam's API as the interface between Goldberg's already-separated client and server components. EX1003 ¶¶143, 145. That change formalizes the existing network pathway without changing Goldberg's diagnostic logic, uses a routine interface for a known system, and would have had a predictable result. EX1003 ¶146.

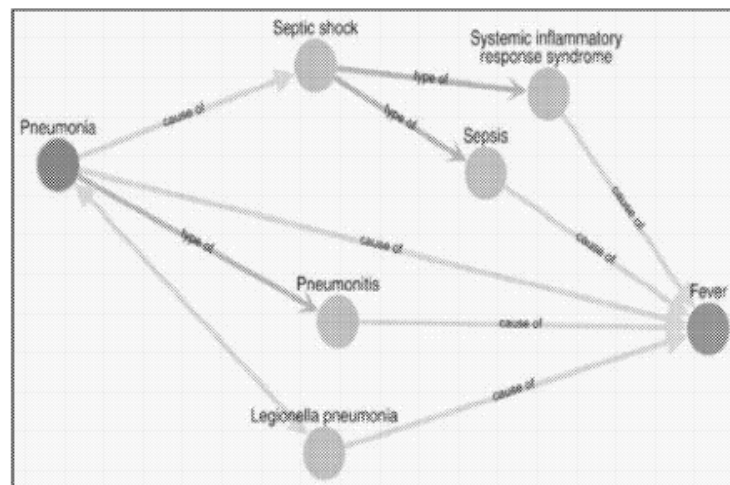
3. Element [1b]: “wherein said knowledge graph includes a plurality of nodes, which include a plurality of medical condition nodes, a plurality of finding nodes, and a plurality of investigation nodes”

Goldberg discloses a knowledge graph containing multiple node types. Goldberg describes integrating SNOMED, LOINC, and clinical probability data into “a new hybrid knowledge graph,” stored in “a database for storage of medical hybrid knowledge graph.” EX1006, 6:20-40, 12:44-54; EX1003 ¶148. Goldberg discloses a “medical knowledge graph” with six node sets: diseases, associated conditions, symptoms, complications, laboratory tests, and treatments, connected by “a plurality of connectors” derived from ontological and clinical relationships. EX1006, 15:55-16:35; EX1003 ¶149. Goldberg further discloses pathways containing laboratory-test nodes and determining “a specific laboratory test . . . to be administered” from those pathways. EX1006, 16:55-17:5; EX1003 ¶150. Diseases, associated conditions, and complications are medical condition nodes; symptoms and signs are finding nodes; and laboratory tests are investigation nodes. EX1003 ¶¶148-150.

FIG. 1's Celiac-disease rule table provides the same single-graph mapping, with ASSOCIATED CONDITION, COMPLICATION, and LABORATORY TESTS rows. EX1006, FIG. 1; EX1003 ¶¶151-152. FIG. 4 adds SYMPTOM/COMPLAINT, SIGNS, and RISK FACTORS entries, including “Abdominal pain (finding)” and “Ataxia (finding).” EX1006, FIG. 4, 9:1-10; EX1003 ¶¶153-154.

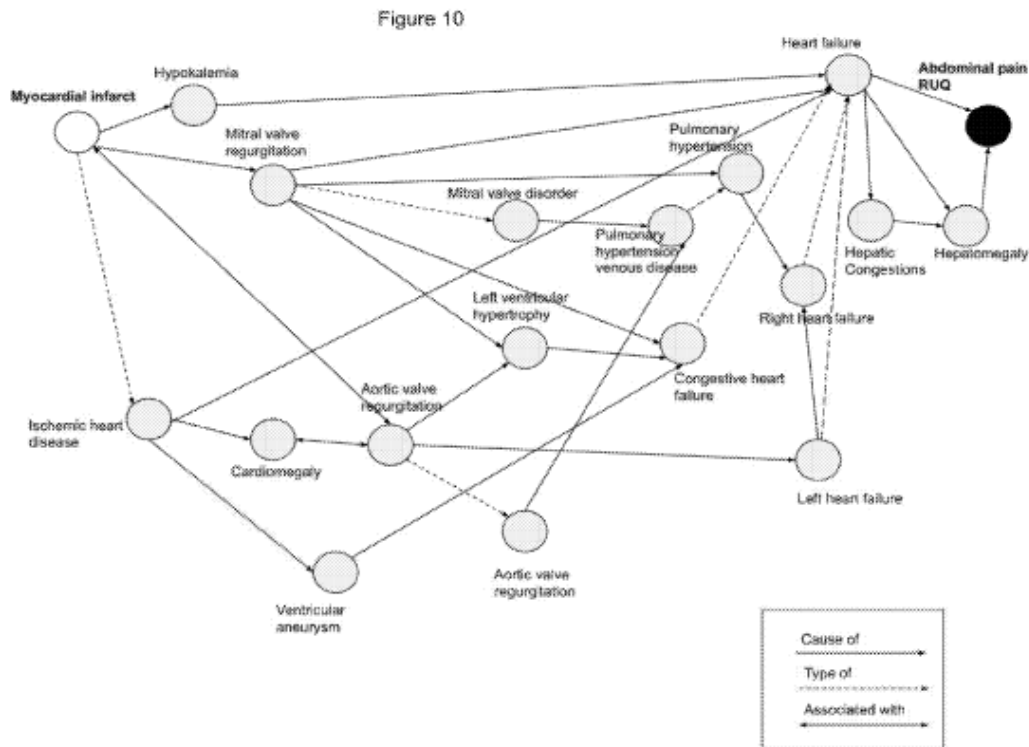
Goldberg's FIG. 9 is “an example of a hybrid graph showing clinical relations connecting Pneumonia and Fever.” EX1006, 5:5-7; EX1003 ¶156. The darker arrows represent SNOMED “type-of” relations, while the lighter arrows reflect clinical relations. *Id.* 10:4-12, FIG. 9; EX1003 ¶156. This is a concrete example of finding and condition nodes connected in the same graph. EX1003 ¶¶155, 159.

FIG. 9

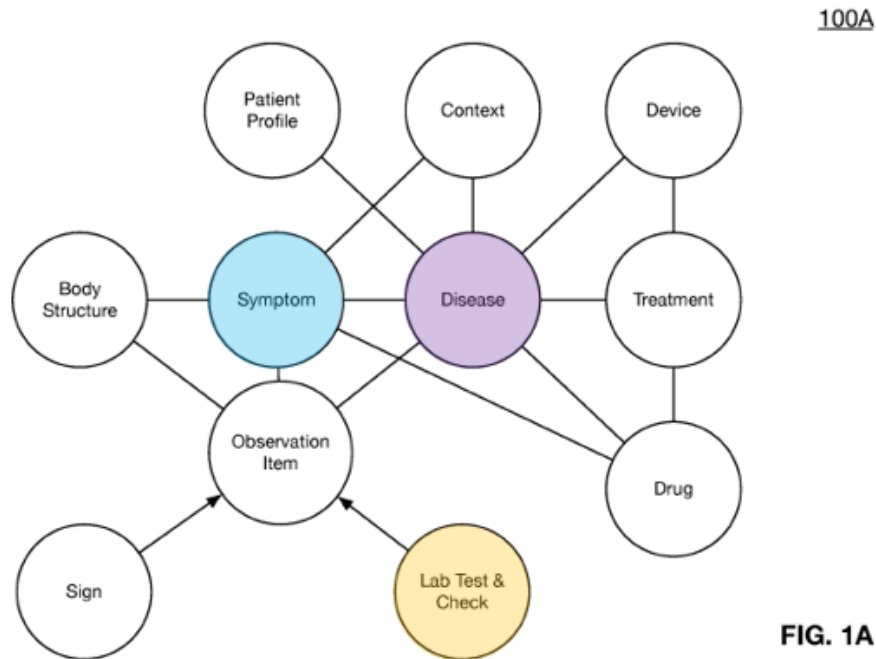


EX1006 FIG. 9

FIG. 10 provides another example with approximately nineteen nodes and connections illustrating traversal across both ontological and clinical edges among condition and finding concepts. EX1006, 10:5-20, FIG. 10; EX1003 ¶¶157-159.



To the extent Goldberg does not show the claimed nodes and relationships (which it does), Dang also discloses these. EX1003 ¶160. Dang's FIG. 1A identifies "Lab Test & Check" as a dedicated node type alongside Disease, Symptom, Sign, and Observation Item, with directional edges connecting the types. EX1008 ¶[0027], FIG. 1A; EX1003 ¶160.



EX1008 FIG. 1A (annotated)

FIG. 1B depicts a three-tier graph: factual nodes include “symptom nodes $\{s_1, s_2, s_3 \dots s_m\}$; context nodes $\{c_1 \dots c_p\}$, and test nodes $\{t_1, t_2 \dots t_j\}$ ”; those nodes connect through feature nodes to disease nodes $\{d_1, d_2, d_3 \dots d_n\}$. EX1008 ¶¶[0027]-[0031], FIG. 1B. Thus, Dang separately represents finding-related and investigation-related factual nodes while connecting them to medical-condition nodes. EX1003 ¶161.

100B

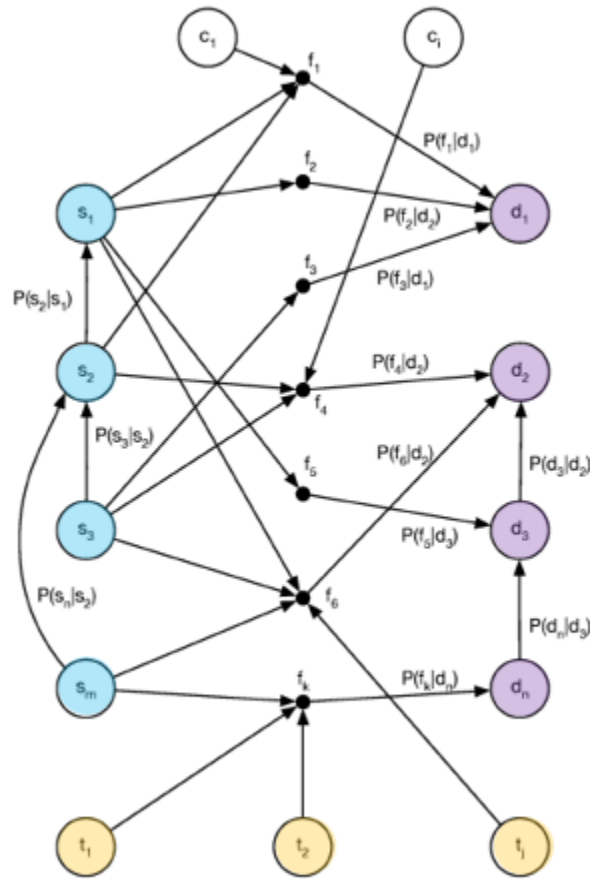


FIG. 1B

EX1008 FIG. 1B (annotated)

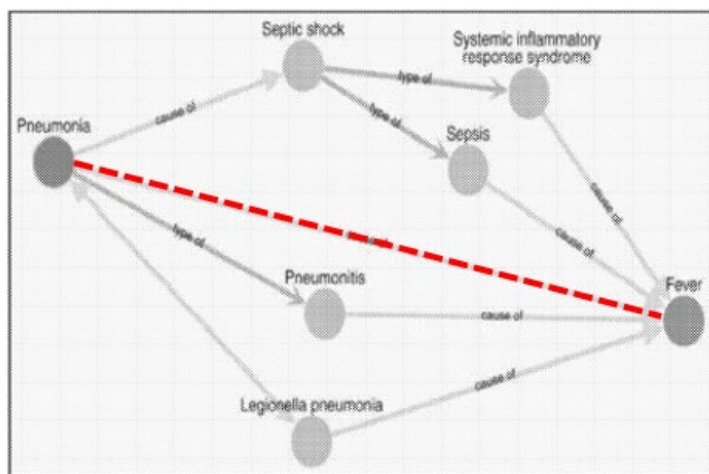
Goldberg already recites laboratory tests as a distinct node set but does not depict every node category in a figure. A POSITA would have used Dang's explicit factual-feature-disease topology to implement those categories in Goldberg's hybrid graph because it makes the categories available for automated traversal and diagnostic inference. EX1003 ¶162. This would preserve Goldberg's evidence graph and pathway logic while supplying a conventional graph representation, with a predictable result. *Id.*

4. **Element [1c]: “wherein at least one of said finding nodes in said knowledge graph is traversable to a first medical condition node to indicate that a finding represented by said at least one of said finding nodes is associated with a first medical condition represented by said first medical condition node”**

Under its plain meaning, “traversable to” requires a connected path in the graph from the finding node to the condition node, including through intermediate nodes. EX1003 ¶170.

Goldberg discloses a finding node traversable to a first medical condition node. Goldberg explains that the system can, for example, track jaundice back to a complication and then to the originating liver disorder. EX1006, 8:31-39; EX1003 ¶164. FIG. 9 separately shows a clinical relation connecting Fever with Pneumonia; the darker SNOMED “type-of” arrows and lighter clinical arrows identify the traversable relationships. EX1006, 10:3-12, FIG. 9; EX1003 ¶165.

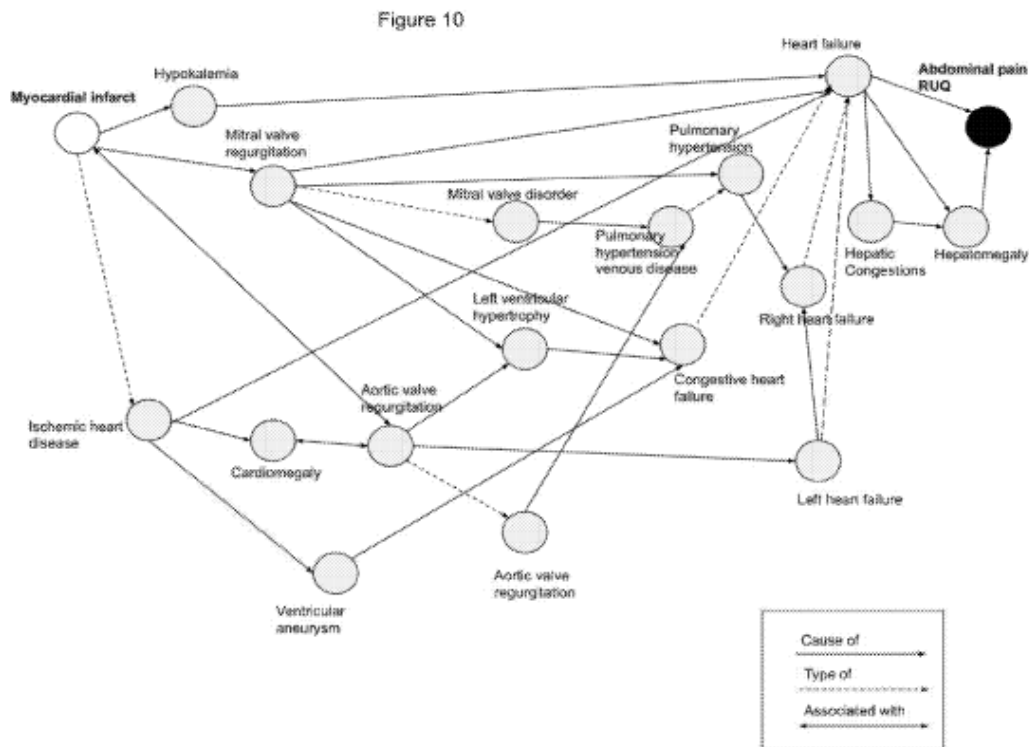
FIG. 9



EX1006, FIG. 9 (annotated)

The Fever node is traversable to the Pneumonia node, indicating that the finding is associated with that condition. EX1003 ¶165.

FIG. 10 shows paths connecting Myocardial infarction and abdominal pain through “Type of” and “Cause of” relationships. EX1006, 10:5-20, FIG. 10; EX1003 ¶166.



Goldberg defines pathways by selecting connectors that connect pairs of nodes, with connectors derived from ontological and clinical relationships. EX1006, 14:35-46, 15:40-65; EX1003 ¶167.

To the extent Goldberg does not expressly disclose the claimed traversability (which it does), Dang illustrates the same mapping: FIG. 1A connects a Symptom node to a Disease node, and FIG. 1B shows s_1 traversable to d_1 and s_2 traversable to d_1 and d_2 . EX1008 ¶¶[0027]-[0031], FIGS. 1A-1B; EX1003 ¶168. A POSITA would have used Dang's explicit finding-to-disease paths in Goldberg for the reasons explained above in Section IX.A: both systems use graph relationships for diagnosis, and Dang makes explicit the traversal that Goldberg already supports. EX1003 ¶¶127, 129, 168.

5. Element [1d]: “wherein at least one of said investigation nodes in said knowledge graph is traversable to a second medical condition node to indicate that an investigation represented by said at least one of said investigation nodes is associated with a second medical condition represented by said second medical condition node”

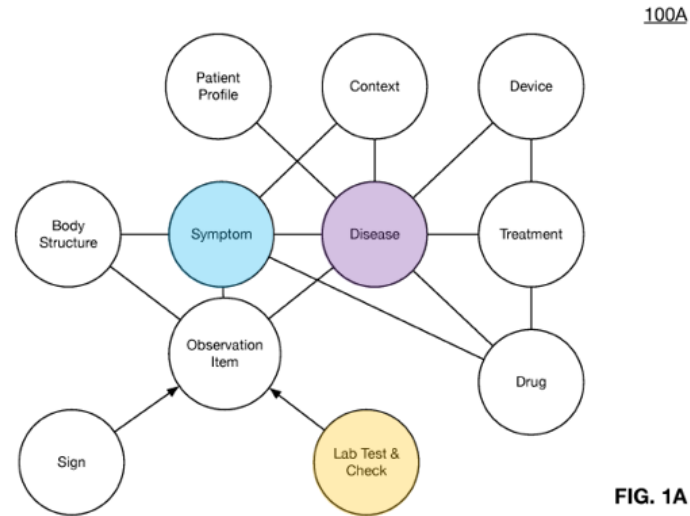
Under its plain meaning, “traversable to” requires a connected path in the graph from the investigation node to the condition node, including through intermediate nodes. EX1003 ¶170.

Goldberg's claim 9 recites a “fifth set of nodes representing the plurality of laboratory tests.” EX1006, 16:8-24; EX1003 ¶171. Claim 11 recites pathways containing laboratory-test nodes and determining “a specific laboratory test ... to be administered to the patient” from those pathways. EX1006, 16:60-17:3; *see also id.*, 17:30-18:15; EX1003 ¶171. Goldberg also states that multiple pathways may be searched for Pneumonia and that the system may show “all associations with

findings, lab tests, etc.” EX1006, 11:55-67; EX1003 ¶172. These disclosures show paths between laboratory-test nodes and disease nodes, including traversal in either direction. EX1003 ¶¶171-172.

Goldberg’s FIG. 1 table shows that the LABORATORY TESTS rule links Celiac disease to “Amylase [Enzymatic activity/volume] in Serum, Plasma or Blood: HIGH” with a probability of 5-10. EX1006, FIG. 1, 6:65-7:2; EX1003 ¶173. FIG. 4 lists Amylase: HIGH, Ceruloplasmin: LOW, and Endomysium Ab: HIGH alongside condition, complication, symptom, and sign entries. EX1006, FIG. 4, 9:1-12; EX1003 ¶174. Thus, Amylase is an investigation node traversable to Celiac disease, which is a second medical condition node distinct from the Pneumonia node discussed for element [1c], within the same unified graph. EX1003 ¶175.

To the extent Goldberg is found not to expressly depict the investigation-to-condition path, Dang supplies additional support. Dang’s FIG. 1A shows a “Lab Test & Check” investigation node traversable to a Disease node. EX1008 ¶[0027], FIG. 1A; EX1003 ¶176.



EX1008 FIG. 1A (annotated)

Dang's FIG. 1B shows test nodes $t_1, t_2 \dots t_j$ traversable through the graph to disease nodes. EX1003 ¶¶176-177. For example, in FIG. 1B, test node t_2 connects to feature node f_k , which connects to disease node d_n through $P(f_k|d_n)$. EX1008 ¶[0031], FIG. 1B; EX1003 ¶178.

100B

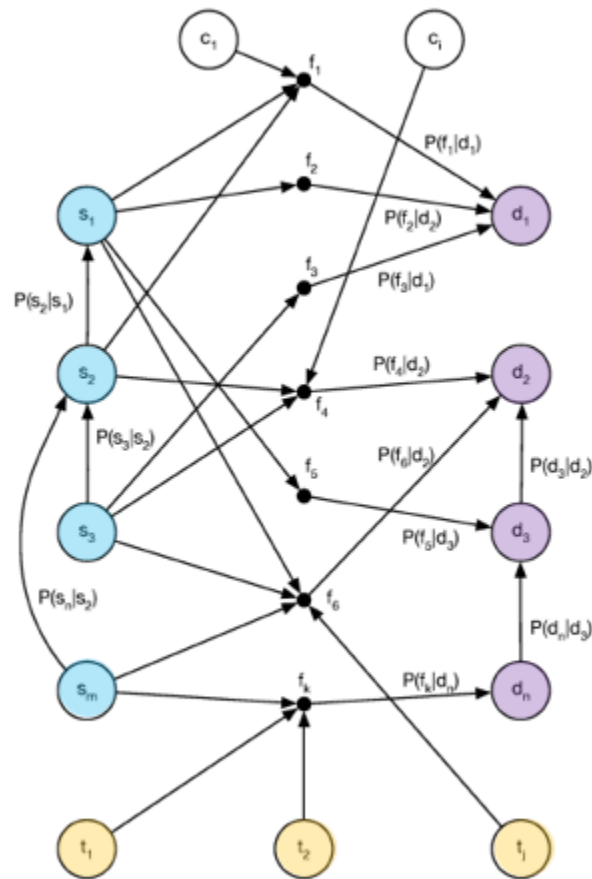


FIG. 1B

EX1008 FIG. 1B (annotated)

Dang's claim 7 recites "detecting a set of factual nodes in a knowledge graph data structure; inferring a set of evidential nodes in the set of factual nodes; inferring a set of disease feature nodes in the set of evidential nodes; and inferring a set of possible disease nodes in the set of diseases feature nodes." EX1008, claim 7; EX1003 ¶178. Dang explains that its process detects factual nodes, including "symptom nodes, test nodes, context nodes," at step 502, then infers evidential nodes at step 504, disease-feature nodes at step 506, and possible disease nodes at step 508.

EX1008 ¶¶[0047]-[0050], FIG. 5; EX1003 ¶178. A POSITA would have used this explicit traversal to implement Goldberg's test-to-condition paths because it provides a natural graph topology for the investigation relationships Goldberg already recites and would enable more reliable automated traversal with less ambiguity. EX1003 ¶¶129, 162, 179.

6. Element [1e]: “wherein one or more of said nodes in said knowledge graph are extracted from a plurality of medical evidence sources and are linked to a medical terminology ontology”

Goldberg discloses extraction from multiple evidence sources. Goldberg discloses “the translation of medical knowledge from multiple sources (e.g., books, articles, publications, personal knowledge etc.), into a hybrid knowledge graph which integrates clinical knowledge along with other ontology based knowledge graphs, such as SNOMED, LOINC or other types of medical databases.” EX1006, 5:51-62; EX1003 ¶182. Goldberg discloses that “[d]ata is derived from evidence-based or other sources” and that “[e]ach such association within the knowledge base has a source such as textbook, article etc.” EX1006, 6:35-44; EX1003 ¶183. Thus, the nodes and relationships in Goldberg's hybrid knowledge graph are extracted from a plurality of medical evidence sources. EX1003 ¶¶181-183.

Goldberg also identifies the ontology links; in Goldberg, a first graph is derived from a healthcare ontology such as SNOMED; a second is derived from “an ontology dedicated to laboratory tests and procedures (e.g., LOINC)”; and a third is

built by medical experts researching medical publications to create a clinical probability graph. EX1006, 6:10-30; EX1003 ¶184. FIGS. 8A-8B show sources including Harrison's Principles of Internal Medicine and journal citations, and Goldberg states that publication content may be integrated "by automated tools, optionally in cooperation with human editors." EX1006, FIGS. 8A-8B, 10:60-63; EX1003 ¶¶185-186. Thus, the same graph has nodes extracted from multiple evidence sources and linked to SNOMED/LOINC terminology ontologies. EX1003 ¶187.

7. Element [1f]: "wherein said knowledge graph is configured to support reasoning capability by allowing traversal of ancestor-descendant relationships among one or more of said medical condition nodes, said finding nodes, or said investigation nodes"

Goldberg's hybrid graph supports the claimed ancestor-descendant traversal through SNOMED's "is-a" hierarchy. FIG. 6 shows Bacterial Pneumonia is-a Infective Pneumonia is-a Pneumonia, and FIG. 7 shows "is-a" edges among Myocardial infarction, Ischemic heart disease, and Myocardial disease. EX1006, FIGS. 6-7, 9:50-60; EX1003 ¶¶189-190. Goldberg also describes an "Is a" or "Sub-type" relation, including iron-deficiency anemia as a subtype of anemia. EX1006, 10:35-50; FIG. 11; EX1003 ¶191. Goldberg's diagnostic paths use SNOMED "type-of" relations alongside clinical relations. EX1006, 10:3-23, FIGS. 9-10; EX1003 ¶¶156, 196. These parent-child edges connect condition and finding concepts and

allow the data processing engine to traverse the graph. EX1003 ¶¶191-192. That operation is consistent with the '883 patent's description of SNOMED and LOINC as providing reasoning. EX1001, 5:13-19, 8:38-58; EX1003 ¶193.

Dang provides additional support for applying hierarchical reasoning during diagnosis. Dang identifies evidential nodes “based on hyponymy relationships between at least two factual nodes.” EX1008 ¶[0010], claim 9; EX1003 ¶194. Dang explains that hyponymy relates a generic term, the hypernym, to an instance, the hyponym, and that the hypernym is broader. EX1008 ¶[0048]; EX1003 ¶194. Its factual nodes include “symptom nodes, test nodes, context nodes,” and the process reasons through those relationships to infer evidential nodes, feature nodes, and possible diseases. EX1008 ¶¶[0047]-[0050]; EX1003 ¶194. Hypernym-hyponym is a parent-child relation, so applying Dang's repeated traversal to Goldberg's SNOMED-linked graph would reach relevant ancestors and descendants. EX1003 ¶195. Goldberg already has type-of and subtype relationships; Dang shows using those relationships during inference. The combination would therefore be a predictable use of existing graph relationships for the same diagnostic purpose. EX1003 ¶196.

- 8. Element [1g]: “wherein said medical terminology ontology includes a Systemized Nomenclature of Medicine–Clinical Terms (SNOMED-CT) database, or a Logical Observation Identifiers, Names, and Codes (LOINC) database”**

Goldberg expressly identifies both claimed terminology ontologies. It describes SNOMED as “an encompassing Ontology covering hundreds of thousands of medical terms” and LOINC as “an ontology dedicated to laboratory tests and procedures.” EX1006, 1:54-56, 6:5-28; EX1003 ¶198. Goldberg’s FIG. 1 further shows the LOINC-coded test name “Amylase [Enzymatic activity/volume] in Serum, Plasma or Blood.” EX1006, FIG. 1, 6:65-7:2; EX1003 ¶217. Thus, SNOMED supplies the clinical concept hierarchy and LOINC supplies standardized laboratory-test terminology. EX1003 ¶198. The ’883 patent admits that SNOMED-CT and LOINC were known, pre-existing ontologies. EX1001, 4:12-27, 5:4-19; EX1003 ¶199.

- 9. Element [1h]: “identifying, using said reasoning capability, a set of ancestor–descendant relationships of said knowledge graph that are relevant to said medical query, wherein said reasoning capability including traversing said knowledge graph to identify one or more of said medical condition nodes, said finding nodes, or said investigation nodes that are relevant to said medical query”**

Element [1h] requires using the same “reasoning capability” recited in element [1f] to identify ancestor-descendant relationships relevant to the medical query, where that reasoning includes traversing the graph to identify relevant condition, finding, or investigation nodes. The ’883 patent’s reasoning service

performs this function by using an “internal or external taxonomy or any other suitable medical hierarchy” to expand a query to related concepts; for example, a diagnostic factor of “double quotidian fever” is traversed upward to its parent “fever.” EX1001, 23:59-24:15; EX1003 ¶205. Goldberg’s diagnostic algorithm performs the same operation over the SNOMED hierarchy discussed for element [1f]. *Supra* §IX.B.7.

Goldberg defines pathways in the graph “by selecting one or more connectors that connect the pair of nodes,” where the connectors are derived from ontological and clinical relationships between medical terms, and selects connectors representing aspects of the patient’s health data. EX1006, 16:22-38. Because Goldberg’s ontological connectors are SNOMED “is-a” or “type-of” relations, selecting pathways in response to a particular patient’s data uses the graph’s ancestor-descendant structure and identifies the ancestor-descendant relationships relevant to that query. EX1003 ¶¶201-202. Goldberg’s figures confirm that its query paths run through those hierarchical edges: FIG. 9 combines SNOMED “type-of” relations with clinical relations in the graph connecting Pneumonia and Fever, and FIG. 10 connects Myocardial infarction and abdominal pain through paths that include “Type of” edges. EX1006, 10:3-20, FIGS. 9-10; EX1003 ¶¶156, 166.

Goldberg’s reasoning also traverses the graph to identify the relevant nodes. Goldberg returns a “path to decision” and, for example, tracks jaundice back through

a complication to the originating liver disorder. EX1006, 8:31-46; EX1003 ¶202. Goldberg searches “multiple pathways” when looking up Pneumonia, shows “all associations with findings, lab tests, etc.,” and provides “patient-tailored reference lookup.” EX1006, 11:55-12:10; EX1003 ¶¶202-203. These traversals identify the condition, finding, and investigation nodes relevant to the patient’s query. EX1003 ¶202.

To the extent Goldberg does not expressly disclose element [1h], Dang does. Dang’s process begins with “data from a set of patient complaint records,” detects factual nodes (including symptom, test, and context nodes) using “semantic analysis and matching” with “Confidence of fact=similarity(input->node),” and treats the patient’s complaint as the medical query. EX1008 ¶¶[0009], [0047]; EX1003 ¶207. Dang then “infer[s] (step 504) evidential nodes” using reasoning through hyponymy, infers disease-feature nodes at step 506, and infers possible diseases at step 508, with confidence values at each stage. EX1008 ¶¶[0048]-[0050], FIG. 5; EX1003 ¶208. Dang also states that “disease information may be aggregated through hyponymy analysis.” EX1008 ¶[0051]; EX1003 ¶208. Because the reasoning runs on nodes matched from the patient’s input, the relationships identified are relevant to that query. EX1003 ¶208. As explained for element [1f], Dang’s hypernym-hyponym relationships are ancestor-descendant relationships. *Supra* §IX.B.7; EX1003 ¶195.

A POSITA would have been motivated to use Dang’s query-time hyponymy reasoning within Goldberg’s pathway selection, which already operates over SNOMED “type-of” relations, so that a patient’s specific finding could be matched to broader findings stored in the graph, and the reverse. EX1003 ¶209. Both references reason over the same kind of graph for the same purpose—identifying candidate diseases from a patient’s findings—so the result would have been predictable. *Id.*; *supra* §IX.A.

10. **Element [1i]: “outputting, responsive to said medical query, an output to said software application, wherein said output includes data related to one or more of said medical condition nodes, said finding nodes, or said investigation nodes that are relevant to said medical query in order for said software application to generate a medical determination”**

Goldberg’s App “generates a list of suspected diseases and complications” and “suggests the next best step to narrow down that list.” EX1006, Abstract, 7:25-50; EX1003 ¶212. The output therefore includes data related to relevant condition nodes and investigation nodes, such as the recommended test when Goldberg says the system may “recommend test A over test B.” EX1006, 8:20-32; EX1003 ¶253. Goldberg further offers physicians “a way to make an updated, evidence-based clinical decision.” EX1006, 7:19-24; EX1003 ¶311.

Gnanasambandam supplies the API delivery: its published APIs provide analytics to consuming applications, including data for a diagnosis of a medical

condition, delivered to client devices running the autonomous multipurpose application for presentation. EX1007, 100:24-34, 101:12-37, 102:22-24, 101:66-102:5, 62:13-15; EX1003 ¶211. In the combination, the differential and next-step output travels through the API to App 230, which uses it to generate a medical determination. Using the API as transport for Goldberg's existing output would have been predictable. EX1003 ¶213.

C. Claim 2: “A method as recited in claim 1 wherein each of said investigation nodes is linked to a corresponding result node ...”

Claim 2 recites: “A method as recited in claim 1 wherein each of said investigation nodes is linked to a corresponding result node holding a result of said each investigation node, each of said corresponding result nodes being linked to said at least one of said medical condition nodes to which said each investigation node is linked.” The '883 patent explains that an EDI Result node holds a condition-specific result, such as “low” in node 326, and sits between the investigation group and the EDI node, forming the chain Condition → Investigation Group → EDI Result → EDI. EX1001, 18:28-43; 19:14-24; 21:57-67; 22:1-11; EX1003 ¶¶215-216.

Goldberg's FIG. 1 likewise lists, under “LABORATORY TESTS,” “Amylase [Enzymatic activity/volume] in Serum, Plasma or Blood: HIGH” for Celiac disease, with a probability of 5-10. EX1006, FIG. 1, 6:65-7:2; EX1003 ¶217. The colon-delimited “:HIGH” separates the condition-specific result qualifier from the condition-independent test identity. EX1003 ¶¶217, 220.

Celiac disease (disorder)	LABORATORY TESTS	Amylase [Enzymatic activity/volume] in Serum, Plasma or Blood:HIGH	5-10	1	https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3493881/
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EX1006 FIG. 1 (excerpted and annotated)

FIG. 4 confirms the same mapping by pairing “Amylase: HIGH” and “Ceruloplasmin: LOW” with particular conditions. EX1006, FIG. 4, 9:1-10; EX1003 ¶219.

LABORATORY TESTS	Amylase [Enzymatic activity/volume] in Serum, Plasma or Blood:HIGH	5-10	
COMPLICATION	Anemia of chronic disorder (disorder)		5-10
SIGNS	Ataxia (finding)	1-2	
ASSOCIATED CONDITION	Autoimmune hepatitis (disorder)	1-2	5-10
LABORATORY TESTS	Ceruloplasmin [Mass/volume] in Serum or Plasma:LOW	2-5	

EX1006 FIG. 4 (excerpted and annotated)

“HIGH” is the same type of information that the ’883 patent describes as the content of a result node: a value such as “high” or “low” indicating the outcome of a test for a particular condition. EX1001, 21:57-22:21; EX1003 ¶218. Thus, Goldberg’s Amylase test is the investigation node, its “HIGH” qualifier is the corresponding result node or result data, and the Celiac-disease rule links that result to the condition node. EX1003 ¶¶218-220.

To the extent Goldberg does not implement the qualifier as a structurally distinct node, a POSITA would have found that implementation obvious because separating test identity from result interpretation is a fundamental graph-design

principle that preserves reusable test nodes while allowing condition-specific results to vary. EX1003 ¶¶221-222. Dang discloses “an observation item node” and “a lab test and check node” connected by “[d]irectional edges” that “indicate a flow of information from one node to another.” EX1008 ¶¶[0027], [0036], FIG. 1A; EX1003 ¶223. Dang’s Observation Item node sits between the Lab Test & Check node and the Disease node, providing a predictable intermediate result structure. EX1003 ¶223. A POSITA would have used that structure here to keep the laboratory-test node reusable while holding the result in its own node and permitting traversal from the test, through the result, to the associated condition. EX1003 ¶223.

D. Claim 3: “A method as recited in claim 2 wherein each of said investigation nodes represents a laboratory test or an examination, and wherein said result node ... represents a result of said laboratory test or said examination”

Goldberg’s investigation nodes represent laboratory tests. In FIG. 1, the Amylase test appears under “LABORATORY TESTS” and is identified by the LOINC-coded test name “Amylase [Enzymatic activity/volume] in Serum, Plasma or Blood.” EX1006, FIG. 1, 6:20-28, 6:65-7:2; EX1003 ¶225. That entry identifies the laboratory test itself, satisfying claim 3’s requirement that each investigation node represents a laboratory test or examination. EX1003 ¶225. Goldberg then appends the result qualifier “:HIGH” to the test name for the Celiac-disease rule. EX1006, FIG. 1, 6:65-7:2. As Dr. Musen explains, “HIGH” represents the result of the Amylase laboratory test—the condition-specific outcome indicating elevated

Amylase associated with Celiac disease—rather than a second description of the test identity. EX1003 ¶226.

The same mapping appears in FIG. 4, which lists “Amylase: HIGH” and “Ceruloplasmin: LOW.” EX1006, FIG. 4, 9:1-10. Each entry pairs a laboratory test with a result qualifier linked to a particular condition, so the test is the claimed investigation node and the qualifier is the corresponding result node or result information. EX1003 ¶¶219, 225-226.

To the extent the claim requires a separately represented result node, Dang supplies an express structural model through its distinct “Observation Item” and “Lab Test and Check” node types connected by “[d]irectional edges.” EX1008 ¶¶[0027], [0036], FIG. 1A; EX1003 ¶223. That implementation would have been a predictable way to represent Goldberg’s test-and-result pairs without changing the underlying diagnostic analysis. EX1003 ¶¶223, 225-226.

E. Claim 4: “A method as recited in claim 1 wherein said finding nodes are diagnostic factor nodes”

The ’883 patent defines a diagnostic factor as information that “the physician can observe, detect or measure quickly or have the patient describe to him during an office visit,” i.e., traditional signs and symptoms. EX1001, 9:21-28.

Goldberg discloses precisely those types of findings. For example, Goldberg’s claim 9 recites “a third set of nodes representing the plurality of symptoms.” EX1006, 16:8-24; EX1003 ¶229. FIG. 4 separately identifies the categories

“SYMPTOM/COMPLAINT,” including “Abdominal pain (finding),” and “SIGNS,” including “Ataxia (finding).” EX1006, FIG. 4, 9:1-12; EX1003 ¶230. FIG. 10 provides additional finding nodes, including Abdominal pain RUQ, Hepatomegaly, Cardiomegaly, and Left ventricular hypertrophy, each representing a clinical observation or physical finding that a physician can detect during an examination. EX1006, FIG. 10, 10:13-23; EX1003 ¶231.

Goldberg then uses these findings as diagnostic inputs: “[u]pon a list of given history, symptoms, signs and other clinical features the app generates a list of suspected diseases and complications.” EX1006, 7:27-30; EX1003 ¶232. Goldberg’s application therefore treats symptoms and signs as patient-specific diagnostic factors, matches them to finding nodes, and uses their associations to generate suspected medical conditions. EX1003 ¶232.

F. Claim 5: “A method as recited in claim 1 wherein said software application is an artificial intelligence (AI) application”

Goldberg discloses an AI-based diagnostic application through both its inference algorithm and its machine-learning rule-generation process. Goldberg states that the application uses “a mathematical inference algorithm that finds the most likely explanation for the patient’s condition.” EX1006, 8:14-21. It further explains that “[a]pp algorithms are used that are based on mathematical inference computations adapted to handle the large number of associations between the various clinical features.” EX1006, 7:29-42. Goldberg also states that “AI and

machine learning algorithms can be applied to large sets of individual patient records to look for patterns and create ‘clinical rules derived from big data’” that are added to the hybrid knowledge graph. EX1006, 14:7-18. These disclosures describe artificial-intelligence analytics applied to patient data and a medical knowledge graph, not merely a static database lookup. EX1003 ¶234.

To the extent Goldberg’s user-facing application is not expressly labeled an AI application, Gnanasambandam supplies the express disclosure: claim 1 recites “publishing, for implementation in the autonomous multipurpose application, at least one API that uses artificial intelligence to perform analytics based on a knowledge graph pertaining to ontological data of a medical condition.” EX1007, claim 1; EX1003 ¶¶235-236. Gnanasambandam further states that its AI engine uses “one or more machine learning models.” EX1007, 18:30-39; EX1003 ¶236. A POSITA would have been motivated to use Gnanasambandam’s AI-enabled application and API layer with Goldberg’s existing AI-based diagnostic engine because both references independently employ artificial intelligence for medical knowledge-graph analytics. The combination would merely apply Gnanasambandam’s API delivery mechanism to Goldberg’s existing inference and machine-learning functionality, with no change to the diagnostic objective or graph. EX1003 ¶¶233-238.

G. Claim 6: “said medical query includes at least one patient diagnostic factor extracted from an electronic health record (EHR) ... matching said patient diagnostic factor to one of said finding nodes ...”

Goldberg receives a patient’s “history, symptoms, signs and other clinical features” and uses “the inputs and their corresponding associations within the knowledge base to run a mathematical inference algorithm that finds the most likely explanation for the patient’s condition.” EX1006, 7:25-40, 8:15-25; EX1003 ¶240. These inputs correspond to the history, symptoms, signs, and laboratory results ordinarily recorded in an EHR. EX1003 ¶243. Goldberg’s matching workflow therefore supplies the claimed operation: patient-specific diagnostic factors are matched to corresponding symptom and sign finding nodes, and the resulting associations produce a list of suspected diseases and complications. EX1003 ¶¶240-241. Goldberg also states that the application “suggests the next best step” to narrow that list. EX1006, 7:30-45; EX1003 ¶241.

Goldberg references the role of EHR systems in healthcare, but it does not expressly state that its application extracts the diagnostic factors from an EHR. EX1006, 1:46-2:9; EX1003 ¶243. Gnanasambandam discloses receiving “an electronic medical record (EMR) including notes pertaining to a patient,” processing those notes to obtain indicia such as “a word, a cardinal, a phrase, a sentence, a predicate, or some combination thereof,” and identifying a possible condition “by identifying a similarity between the indicia and a knowledge graph representing

knowledge pertaining to the possible medical condition.” EX1007, 125:10-29, 56:61-57:45, FIG. 25; EX1003 ¶244. Gnanasambandam further explains that EMRs may be provided directly to the cognitive engine or retrieved through an API and that patient notes may be extracted from the EMRs. EX1007, 53:4-12; EX1003 ¶245. The AI engine learns from “evidence-based guidelines, clinical trials, physician research, electronic medical records.” EX1007, 8:24-37; EX1003 ¶246.

A POSITA would have been motivated to connect Goldberg’s existing matching workflow to Gnanasambandam’s EMR-retrieval architecture because Goldberg already processes the same categories of clinical data that EHRs contain, while Gnanasambandam expressly provides the architecture for receiving and processing that data. EX1003 ¶247. Integrating EHR data as an input for a clinical decision-support system was a routine and predictable implementation. EX1003 ¶247. Dang provides additional confirmation by describing an electronic medical record indicating “a runny nose, a fever.” EX1008 ¶[0036]; EX1003 ¶248. Thus, the combined system extracts a patient diagnostic factor from an EHR, matches it to a finding node, and uses the matched factor to generate the condition output. EX1003 ¶¶247-248.

H. Claim 7: “said medical query is a clinical state ... [and] said output is an unknown diagnostic factor ...”

Claim 7 adds three related limitations: the query is a clinical state containing a likely medical condition and a diagnostic factor; the system matches that factor to a finding node; and the output is an unknown diagnostic factor. EX1003 ¶250.

Goldberg discloses the first two limitations. Goldberg’s application receives patient history, symptoms, signs, and other clinical features, then generates “a differential diagnosis list based on inputs entered for a specific patient” and can “rank likely differential diagnosis results by their probabilistic score.” EX1006, 7:25-35, 8:10-24; EX1003 ¶251. At each stage, the patient’s clinical state includes both likely conditions—the ranked differential—and known diagnostic factors—the findings already entered. This state is the input for the next-step recommendation. EX1006, 7:25-42; 8:10-32; EX1003 ¶251. Goldberg also states that the application “uses the inputs and their corresponding associations within the knowledge base” to reach its differential, which requires matching the patient’s reported findings to corresponding finding nodes. EX1006, 8:14-21; EX1003 ¶252. Goldberg’s next step can be information not yet known: it “may recommend test A over test B” because “[a] positive or negative answer for test A would increase the probability of suspected diagnosis.” EX1006, 8:20-32; EX1003 ¶253.

Dang supplies the third requirement. Dang generates “a best next inquiry question, for use in a medical diagnosis process,” based on “likelihood values that a

set of input symptoms exhibits one or more diseases.” EX1008 ¶[0003]; EX1003 ¶254. After generating a suspected-disease list, Dang “selects (step 704) sub-symptoms or attributes as next inquiry candidates” and “selects (step 706) symptoms derived from related diseases as next inquiry candidates.” EX1008 ¶[0056]; EX1003 ¶254. Dang then calculates each candidate’s “degree of distinguish” and selects the candidate with “a maximal degree of distinguish” as the next inquiry. EX1008 ¶[0058], FIG. 7; EX1003 ¶254. The selected symptom or attribute is an unknown diagnostic factor because it is the information the system proposes to obtain from the patient, and it corresponds to a finding node associated with one or more likely conditions. EX1003 ¶255. Dang reports “top-1 diagnostic accuracy of 61.7% and top-3 diagnostic accuracy of 94.0%,” compared with 32.3%/55.9% and 41.1%/47.0% for benchmark methods, while requiring an average of 13.5 questions rather than 27.7 or 16.6. EX1008 ¶[0059]; EX1003 ¶256.

A POSITA would have implemented Goldberg’s open-ended “next best step” using Dang’s concrete selection method because Goldberg expressly states that “there are several alternative ways to implement such an inference engine.” EX1006, 7:38-45; EX1003 ¶256. Dang’s method serves Goldberg’s stated goal of narrowing the differential “by ruling in some diseases or ruling out other high-risk diseases” and reducing “unnecessary tests.” EX1006, 7:25-35, 2:24-30; EX1003 ¶256. The combination would have been predictable because both systems reason over a graph

of diseases and findings and use the result to guide the next diagnostic inquiry.

EX1003 ¶257.

I. Claim 8: “said each investigation node does not include information specific to a medical condition ...”

Goldberg’s laboratory-test nodes are condition-independent test identities, not disease-specific descriptions. This is the case because Goldberg derives them from LOINC, “an ontology dedicated to laboratory tests and procedures.” EX1006, 6:20-28. LOINC defines a test by what it measures—such as the analyte, measurement property, method, or specimen type—not by the condition it may help diagnose. EX1003 ¶259.

Goldberg FIG. 1 illustrates this separation: the test node is identified as “Amylase [Enzymatic activity/volume] in Serum, Plasma or Blood,” which contains no information specific to Celiac disease. The condition-specific information is the probability of 5-10 and the “:HIGH” result qualifier associated with the Celiac-disease rule. EX1006, FIG. 1, 6:65-7:5; EX1003 ¶260. These values reside in the relationship or rule connecting the test to the condition. FIG. 4 confirms the same architecture for other features: “Chronic diarrhea (disorder)” appears with a likelihood of 10-20 for Celiac disease and 5-10 for Crohn’s disease. EX1006, FIG. 4, 9:1-10; EX1003 ¶261. Thus, the feature identity is reused while its condition-specific significance changes. Goldberg’s claim 9 recites “a fifth set of nodes representing the plurality of laboratory tests,” connected to disease nodes through

connectors that carry the relationship and probability information. EX1006, 16:8-35; EX1003 ¶262.

Dang confirms that design by placing disease-specific probabilities $P(f|d)$ on connections between feature and disease nodes rather than in the test nodes themselves. EX1008 ¶¶[0029], [0031]; EX1003 ¶263. A POSITA would therefore understand that Goldberg's investigation nodes do not include information specific to a medical condition. EX1003 ¶¶259-263.

J. Claim 9: “each of said investigation nodes is disambiguated across said plurality of medical condition nodes”

Goldberg's LOINC integration disambiguates each investigation across multiple medical conditions by assigning the laboratory test a single standardized identity. LOINC provides a unique identifier and standardized name for each laboratory test, and Goldberg derives its test nodes from that ontology. EX1006, 6:20-28; EX1003 ¶265. FIG. 1 lists “Amylase [Enzymatic activity/volume] in Serum, Plasma or Blood” under “LABORATORY TESTS” for Celiac disease. FIG. 4 uses the same LOINC-coded test identity in its comparison of Celiac disease and Crohn's disease. EX1006, FIGS. 1, 4; EX1003 ¶266. The identity therefore remains the same when the test is linked to different conditions; only the associated result, likelihood, or relationship changes. EX1003 ¶266.

Goldberg also queries for “all the diseases that share a combination of one or more lab test results.” EX1006, 8:46-57. This query presupposes a single,

unambiguous test concept that can be linked to and retrieved across multiple diseases. EX1003 ¶266. Goldberg's claim 9 confirms this by defining laboratory tests as "a fifth set of nodes" within the graph, rather than creating a different laboratory-test node for every disease. EX1006, 16:8-24; EX1003 ¶267. A POSITA would therefore understand and find obvious that the standardized LOINC identity disambiguates each investigation across the plurality of medical condition nodes. EX1003 ¶¶265-267.

K. Claim 10: "each of said investigation nodes is independent of said at least one of said medical condition nodes"

Goldberg's laboratory-test nodes are independent of any medical condition because they are derived from LOINC and carry LOINC-coded names defined independently of disease, while existing as a separate "fifth set of nodes" connected to disease nodes through typed connectors. EX1006, 6:20-28, 16:8-24, FIG. 1; EX1003 ¶269. Goldberg's hybrid graph integrates three separately derived components: (1) a SNOMED-based ontology graph, (2) a LOINC-based ontology for laboratory tests and procedures, and (3) clinical probability data linking concepts across those ontologies. EX1006, 6:10-34; EX1003 ¶270. The laboratory-test node therefore originates independently from the disease node; the disease-specific relationship is supplied by the connector or rule. EX1003 ¶270.

FIG. 1 illustrates the point: the Amylase test is identified by its LOINC name and connected to Celiac disease through a probability of 5-10. If the Celiac disease

node were removed, the Amylase test node would continue to exist with the same identity and content; only its connection to that condition would be removed. EX1006, FIG. 1; EX1003 ¶271. Goldberg's claim 11 confirms that the system determines "a specific laboratory test in the plurality of laboratory tests to be administered to the patient" from pathways connecting laboratory tests to disease nodes, meaning that the same test node participates in pathways to multiple diseases. EX1006, 16:60-17:3; EX1003 ¶272.

Dang reinforces the architecture with a distinct test-node tier, " $\{t_1, t_2 \dots t_j\}$," separate from the disease nodes, with disease-specific information carried by the connections. EX1008 ¶¶[0027]-[0031], FIG. 1B; EX1003 ¶263. A POSITA would have recognized that preserving this independence makes the test node reusable across conditions and is the predictable implementation of Goldberg's multi-ontology graph. EX1003 ¶¶270-272.

L. Claim 11: "... a data structure different from said each investigation node that is traversable to both said each investigation node and said at least one of said medical condition nodes ... including attributes pertaining to said ... medical condition nodes ..."

Claim 11 recites "a data structure," not a "node." Other claims use "node" when referring to graph nodes, including claim 2's "result node" and claims 1 and 23. The '883 patent states that conditions, factor groups, EDFs, investigation groups, and EDIs "need not necessarily be implemented in a particular data structure shown

or as nodes.” EX1001, 18:5-12. Thus, claim 11 reaches an organized record other than a graph node. EX1003 ¶274.

Goldberg’s FIG. 1 provides exactly that disclosure: each rule is a structured record with fields for “Source Disorder,” “Type of Rule,” “Rule Target,” “Probability,” “Strength of source,” and “Link to source.” EX1006, FIG. 1, 6:65-7:5; EX1003 ¶275. The LOINC-coded laboratory-test identity is the investigation node; the complete rule record is the claimed different data structure. EX1003 ¶276.

Goldberg’s rule record satisfies each remaining requirement. Its Rule Target field identifies and permits traversal to the laboratory test; its Source Disorder field identifies the condition, such as “Celiac disease (disorder)”; and its Probability, Strength of source, and Link to source fields are attributes pertaining to that condition. EX1003 ¶276. FIG. 4 confirms that these values are condition-specific: “Failure to thrive (disorder)” is listed with 60-70 for Celiac and 30-40 for Crohn’s, while Amylase has a value for Celiac and none for Crohn’s. EX1006, FIG. 4; EX1003 ¶277. FIG. 11 likewise depicts rules carrying a rate (R) and typed relationships, including complication, symptom, lab, and risk factor. EX1006, FIG. 11, 10:28-52; EX1003 ¶278. The ’883 patent’s Investigation Group is consistent with that reading because it is a data structure between a condition and an EDI that can hold condition-dependent information such as ranking. EX1001, FIG. 4C, 21:47-61, 22:1-16; EX1003 ¶279.

Dang confirms the predictable implementation: its feature nodes form a distinct intermediate tier between factual nodes, including test nodes, and disease nodes; the feature-to-disease connections carry $P(f|d)$. EX1008 ¶¶[0028]-[0031], FIG. 1B; EX1003 ¶¶280-281. Dang's steps 502-508 then detect test nodes and infer evidential, feature, and disease nodes. EX1008 ¶¶[0047]-[0050]; FIG. 5; claim 7; EX1003 ¶¶282-283. A POSITA would have used that tier to formalize the intermediate relationship already represented in Goldberg's rule records, allowing the diagnostic algorithm to traverse a discrete reasoning step and reuse feature nodes across disease contexts for a more modular, maintainable graph, with a predictable result because both references associate condition-dependent probabilities with observation-disease relationships. EX1003 ¶¶284-286.

M. Claim 12: “at least one of said investigation nodes is traversable to at least two of said medical condition nodes”

Claim 12 has two requirements: (1) an investigation node must be traversable to at least two condition nodes; and (2) the investigation node must lack information specific to those conditions. EX1003 ¶288.

Goldberg satisfies the first requirement. Its claim 9 recites “a fifth set of nodes representing the plurality of laboratory tests” in a graph that also includes disease, symptom, complication, and treatment nodes. EX1006, 16:8-24; EX1003 ¶289. Claim 11 further determines a specific laboratory test from pathways connecting laboratory-test and disease nodes, so the same test can be reached through pathways

for different suspected diseases. EX1006, 16:55-17:10; EX1003 ¶289. FIG. 4 compares Celiac and Crohn's: the same features, including Chronic diarrhea, Iron deficiency anemia, and Failure to thrive, appear with different likelihood ranges for the two diseases. EX1006, FIG. 4; 9:1-5; EX1003 ¶290. Goldberg also retrieves "all the diseases that share" one or more laboratory-test results and describes a Pneumonia lookup showing "all associations with findings, lab tests, etc." EX1006, 8:54-57; 9:1-10; 11:52-67; EX1003 ¶¶290-291.

The second requirement follows from Goldberg's LOINC-derived test identity, which contains no disease-specific information; the probability and result qualifiers reside in the associated rule or connection. EX1006, 6:20-28, FIG. 1; EX1003 ¶¶292-293. Dang confirms the same architecture. EX1008 ¶[0031], FIG. 1B; EX1003 ¶¶294-295. Using one reusable laboratory-test node to inform several diagnoses is therefore the same predictable design choice already reflected in Goldberg's shared laboratory-test pathways. EX1003 ¶295.

N. Claim 13: "a ranking value indicating how likely it is that an investigation ... is indicative of a medical condition"

Goldberg discloses the ranking value required by claim 13. In FIG. 1, the Amylase:HIGH laboratory-test entry has a probability of 5-10, indicating how likely that test result is to indicate Celiac disease; the value is associated with the path between the test and condition rather than with the generic test identity. EX1006, FIG. 1, 6:65-7:2; EX1003 ¶297. FIG. 4 supplies additional likelihood values for the

same features across two conditions, including Chronic diarrhea at 10-20 for Celiac and 5-10 for Crohn's, and Iron deficiency anemia at 5-10 and 5-15, respectively. EX1006, FIG. 4, 9:1-5; EX1003 ¶298. FIG. 11 likewise assigns each rule a rate (R). EX1006, FIG. 11, 10:28-52; EX1003 ¶299.

Goldberg explains that its knowledge base contains probabilistic associations linking features to diseases and that the inference algorithm uses the strength of those associations to find the most likely explanation for the patient's condition. EX1006, 5:67-6:7, 6:10-44, 8:13-46; EX1003 ¶300. Goldberg's claims further describe a displayed probabilistic value, arrows denoting probabilistic linkages, and an aggregated connection strength for pathways. EX1006, 16:57-59, 17:30-39, 18:10-13; EX1003 ¶301.

Dang discloses the same type of value: each disease-feature connection may carry $P(fx|dn)$, the likelihood that feature fx occurs when disease dn is observed. EX1008 ¶[0031], FIG. 1B; EX1003 ¶302. Those disclosures directly map the claimed ranking value to a condition-specific probability or likelihood on the investigation-condition path. EX1003 ¶¶297-302.

O. Claim 14: “at least one condition-dependent attribute of a medical condition”

Claim 14 is broader than claim 13: it requires only one condition-dependent attribute on the path between an investigation and a condition, not necessarily a ranking value. EX1003 ¶304. Goldberg's FIG. 1 supplies several such attributes in

the Amylase rule: Probability 5-10, Strength of source, and Link to source. EX1006, FIG. 1, 6:65-7:2; EX1003 ¶305. FIG. 4 further shows that the values associated with a feature vary by condition, including the different likelihood ranges for Chronic diarrhea and Iron deficiency anemia. EX1006, FIG. 4, 9:1-5; EX1003 ¶306. Goldberg explains that medical publications may be translated into associations indicating “the probability which links each feature with the disease,” that each association has a source such as a textbook or article, and that the knowledge base records the source and its relative strength. EX1006, 5:67-6:7, 6:10-60; EX1003 ¶307. FIG. 11 also shows a rate and relation type for each rule, including complication, symptom, lab, and risk factor. EX1006, FIG. 11, 10:28-53; EX1003 ¶308.

Dang independently defines $P(fx|dn)$ for a particular disease-feature pair, making the value dependent on the associated disease. EX1008 ¶[0031]; EX1003 ¶309. A POSITA therefore would have placed these probabilities, source attributes, and relation types on the rule, edge, or intermediate feature record on the path, rather than in the reusable investigation node, because that preserves one condition-independent test identity while allowing its significance to vary by condition. EX1003 ¶¶305-309.

P. Claim 17: “said software application causes said output to be displayed on a computer to a user”

Goldberg expressly discloses the claimed user-facing display. Goldberg’s Patient Management App provides a user interface for viewing results from the data-processing engine, including suspected diseases, complications, and recommended next steps. EX1006, Abstract, 7:19-47; EX1003 ¶311. FIG. 2 shows inference engine 210 and knowledge base 220 connected to App 230, which displays the returned differential diagnoses and next-step suggestions. EX1006, FIG. 2; EX1003 ¶312. Goldberg further states that the application may show a “path to decision” and a “strength score” reflecting source reliability. EX1006, 8:30-46; EX1003 ¶312.

Gnanasambandam supplies a complementary presentation layer: its home interface summarizes “Chronic conditions” and “Acute issues,” another interface may display “Possible medical condition: Type 2 Diabetes Mellitus,” and the platform may provide a diagnosis to a patient’s or physician’s computing device for presentation. EX1007, 59:60-60:25, 62:1-34, 62:60-64:10, FIGS. 28, 31, 33; EX1003 ¶313. In the combination, Goldberg’s diagnostic output is delivered through Gnanasambandam’s API architecture and displayed by the client application on a computer to the physician or patient. EX1003 ¶314.

Q. Claim 18: “said output is in a data structure suitable for further processing”

Gnanasambandam discloses API-delivered analytics in a form intended for programmatic use. Its consuming applications subscribe to the APIs, receive the analytics, and further process the output. EX1007, 100:24-40, 101:12-37. The platform may provide a diagnosis to a patient’s or physician’s computing device for presentation, compare a patient graph with condition knowledge to generate a care plan, and determine whether a parameter lacks data in a data structure before causing a notification to be presented. EX1007, 15:1-35, 62:1-30, 97:60-98:40, FIG. 87. An API response carrying these organized analytics is necessarily structured for software consumption rather than merely displayed text. EX1003 ¶316.

Goldberg confirms that its output has the requisite organization: inference engine 210 returns differential diagnoses and next-step suggestions, the application can rank differential diagnoses by probabilistic score, and it can recommend test A over test B. EX1006, FIG. 2, 7:25-42, 8:10-32; EX1003 ¶317. A POSITA would therefore have delivered Goldberg’s ranked diagnoses and recommended investigations through Gnanasambandam’s API as a structured response that the receiving application could rank, compare, use to generate a care plan, or otherwise process. EX1003 ¶318.

R. Claim 19: “in response to said output, receiving ... a new patient diagnostic factor ... and outputting ... a new output”

Goldberg discloses the core update sequence in claim 19. Goldberg’s system receives history, symptoms, signs, and other clinical features, generates a list of suspected diseases and complications, and suggests a next-best step such as a test whose positive or negative result would change the probability of a suspected diagnosis. EX1006, 7:25-42, 8:20-32; EX1003 ¶320. Goldberg also describes a “constantly updated differential diagnosis list” and patient-tailored recommendations, meaning that the output is revised as new findings become available. EX1006, 7:29-42; EX1003 ¶320. The mapping is direct: the initial differential and recommended test are the output; the test result or newly reported finding is the new patient diagnostic factor; and the revised differential or recommendation is the new output. EX1003 ¶320. Because Goldberg runs inference using “the inputs and their corresponding associations within the knowledge base,” the new factor is received and processed against the same knowledge graph. EX1006, 8:1-24; EX1003 ¶¶319-322.

Dang generates “a best next inquiry question” and reports diagnostic performance by the number of questions needed to reach a diagnosis. EX1008 ¶¶[0003], [0059]. A method measured by successive questions receives an answer and produces a new diagnostic state before selecting the next question. EX1003 ¶321.

Gnanasambandam discloses a first round of analysis, dynamically formulated follow-up questions, insertion of received answers into the workspace, and several rounds of additional analysis when information remains insufficient. EX1007, 11:20-35, 30:34-33:31, 35:51-36:20, FIG. 7A; EX1003 ¶323.

A POSITA would have implemented Goldberg's updating loop using Dang's next-inquiry selection and Gnanasambandam's iterative API workflow: Goldberg supplies the condition-specific differential and graph associations, Dang supplies a reasoned choice of the next missing factor, and Gnanasambandam supplies the mechanism for receiving the answer and invoking another analysis round. That combination addresses the specific claim sequence without changing Goldberg's diagnostic objective and would have produced the predictable result of a new output after each new patient factor. EX1003 ¶¶321-323.

S. Claim 20: “matching a portion of said medical query to at least one of said medical condition nodes or ... finding nodes to produce said output”

Goldberg expressly matches a portion of the medical query to graph information to produce its output. The Patient Management App receives “history, symptoms, signs and other clinical features,” and the system uses those inputs and their associations in the knowledge base to run a mathematical inference algorithm that finds the most likely explanation for the patient's condition. EX1006, 7:25-40, 8:14-25; EX1003 ¶325. The patient's symptoms and signs correspond to finding

nodes, while the resulting suspected diseases and complications correspond to medical condition nodes; Goldberg then recommends the next best step. EX1006, 7:25-47; EX1003 ¶325. FIG. 5 illustrates the mapping by listing diseases with likelihoods for entered findings such as Failure to thrive and Ataxia. EX1006, FIG. 5; 9:1-20; EX1003 ¶242, 325.

Gnanasambandam describes the same operation in graph terms: it identifies possible medical conditions by finding a similarity between extracted indicia and a knowledge graph representing the possible condition. EX1007, 57:23-27; EX1003 ¶326. Thus, the combined system matches the relevant portion of the query—such as a symptom, sign, or other extracted indicium—to a finding or condition node and uses the associated graph pathways and probabilities to produce the diagnostic output. EX1003 ¶¶325-326.

T. Claim 21: “said knowledge graph includes more than twenty thousand nodes”

Goldberg’s SNOMED integration supplies more than the twenty-thousand-node threshold. Goldberg describes SNOMED as an ontology covering “hundreds of thousands of medical terms,” and its hybrid graph also incorporates LOINC and clinical probability data. EX1006, 1:54-2:1, 6:10-34. Hundreds of thousands of terms is already well more than twenty thousand, even before adding the separate laboratory-test and clinical-rule structures. EX1003 ¶328.

The scale limitation would also have been obvious as routine expansion of Goldberg's disclosed architecture. See *Precision Power, LLC v. Powertec Solutions Int'l, LLC*, PGR2021-00043, Paper 12 at 23 n.12 (PTAB Aug. 3, 2021) ("It is well-settled that '[a] mere duplication of parts is not invention.'" (quoting *In re Marcum*, 47 F.2d 377, 378 (CCPA 1931)); see also *In re Harza*, 274 F.2d 669, 671 (CCPA 1960) ("the mere duplication of parts has no patentable significance unless a new and unexpected result is produced.")). The difference between a graph with fewer than twenty thousand nodes and one with more is simply additional instances of the same condition, finding, and investigation node types. Goldberg states that its Medical knowledgebase 310 is curated by a community of specialists because the amount and growth rate of medical knowledge require many contributors, and that the knowledge base may be updated on an ongoing basis. EX1006, 7:48-8:5, 11:1-20, FIG. 3. A POSITA would therefore have added more conditions with their associated findings and investigations using the same disclosed graph, associations, and traversal techniques. EX1003 ¶329.

This routine scaling produces no new or unexpected result: a graph exceeding twenty thousand nodes would use the same diagnostic algorithm, probabilistic associations, and traversal techniques on a larger collection of the same node types. Goldberg's community-based curation and ongoing-update model provides an express reason to expand the graph as additional medical knowledge becomes

available, not a reason to stop at a smaller size. EX1006, 3:26-32, 7:48-8:5, 11:1-20. Adding each condition together with its related findings and investigations merely duplicates components Goldberg already teaches, while preserving the same operation and clinical purpose. The claim therefore adds a numerical scale to a known architecture, not a distinct technical function. EX1003 ¶330.

U. Claim 22: “said knowledge graph includes more than one hundred thousand nodes”

Goldberg likewise meets claim 22. SNOMED alone is described as covering “hundreds of thousands of medical terms,” which exceeds one hundred thousand nodes, and Goldberg adds LOINC—“an ontology dedicated to laboratory tests and procedures”—as well as clinical probability data linking concepts across the ontologies. EX1006, 1:54-2:9, 6:10-34; EX1003 ¶332.

The same routine-scaling analysis independently renders the threshold obvious. *Precision*, Paper 12 at 23 n.12; *Harza*, 274 F.2d at 671. Moving from fewer than one hundred thousand nodes to more than one hundred thousand adds further medical conditions, findings, and investigations of the same types already disclosed; it does not require a different graph structure, algorithm, association, or traversal technique. Goldberg’s statement that its knowledge base is curated by a community of medical specialists and updated on an ongoing basis supplies the reason to continue adding those components as the medical knowledge base grows. EX1006, 7:48-8:8; 11:1-24. Adding conditions with associated findings and investigations is

therefore mere duplication of disclosed components, with no new or unexpected result, and a clinically useful graph covering a meaningful range of conditions would naturally exceed the claimed threshold. EX1003 ¶¶333-334.

V. Independent Claim 23

Claim 23 recites a system that performs the same functions as claim 1, adding only a database that stores the knowledge graph and one or more processors and memory storing instructions. Goldberg and Gnanasambandam, with Dang where noted, render each element obvious for the reasons given for claim 1 and below. EX1003 ¶335.

1. Element [23pre]: “A system for providing reasoning capability to integrated medical evidence from medical evidence sources, the system comprising”

To the extent limiting, the preamble is met for the reasons given for element [1pre]. *Supra* §IX.B.1. Goldberg’s platform includes “a healthcare knowledge graph database for storing a medical hybrid knowledge graph” and “a data processing engine running a diagnostic algorithm” that selects pathways to generate differential diagnoses, together with user interfaces through which that reasoning is delivered. EX1006, Abstract, 5:42-62, 7:10-52. Gnanasambandam’s platform publishes APIs that perform analytics on medical knowledge graphs. EX1007, 1:32-45, 100:24-34. The combination is therefore a system for providing reasoning capability to integrated medical evidence. EX1003 ¶¶336-337.

2. Element [23a]: “a database that stores a knowledge graph including ... medical condition nodes, ... finding nodes, and ... investigation nodes”

Element [23a] corresponds to element [1b] and adds a database. *Supra* §IX.B.3; EX1003 ¶¶338-339. Goldberg discloses “a database for storage of medical hybrid knowledge graph.” EX1006, 12:45-50. The stored graph includes the six node sets recited in Goldberg’s claim 9—diseases, associated conditions, symptoms, complications, laboratory tests, and treatments—which map to the claimed medical condition, finding, and investigation nodes, as shown in FIGS. 1, 4, 9, and 10. EX1006, 15:55-16:24, FIGS. 1, 4, 9-10. Dang’s distinct Disease, Symptom, and Lab Test & Check node types provide additional support. EX1008 ¶¶[0027]-[0031], FIGS. 1A-1B.

3. Element [23b]: “at least one of said finding nodes ... is traversable to a first medical condition node”

Element [23b] is identical to element [1c]. *Supra* §IX.B.4; EX1003 ¶¶340-341. Goldberg’s Fever node is traversable to its Pneumonia node (FIG. 9), its findings connect to Myocardial infarction through “Type of” and “Cause of” paths (FIG. 10), and its claim 1 defines pathways by selecting connectors between node pairs. EX1006, 10:3-23, 14:43-65, FIGS. 9-10. Dang’s symptom-to-disease paths provide additional support. EX1008, FIGS. 1A-1B.

4. Element [23c]: “at least one of said investigation nodes ... is traversable to a second medical condition node”

Element [23c] is identical to element [1d]. *Supra* §IX.B.5; EX1003 ¶¶342-343. Goldberg’s laboratory-test node set is connected through pathways to disease nodes, and its FIG. 1 links the Amylase test to Celiac disease, a condition distinct from the Pneumonia node discussed for element [23b]. EX1006, 16:8-24, 16:55-17:5, 11:55-67, FIG. 1. Dang’s test-to-feature-to-disease paths provide additional support. EX1008 ¶¶[0027]-[0031], FIG. 1B.

5. Element [23d]: “one or more of said nodes in said knowledge graph are extracted from a plurality of medical evidence sources and are linked to a medical terminology ontology”

Element [23d] is identical to element [1e]. *Supra* §IX.B.6; EX1003 ¶¶344-345. Goldberg translates medical knowledge “from multiple sources (e.g., books, articles, publications, personal knowledge etc.)” into its hybrid graph, states that each association “has a source such as textbook, article etc.,” and integrates SNOMED and LOINC. EX1006, 5:42-62, 6:4-44, 1:54-56, FIGS. 8A-8B.

6. Element [23e]: “said knowledge graph is configured to support reasoning capability by allowing traversal of ancestor–descendant relationships”

Element [23e] is identical to element [1f]. *Supra* §IX.B.7; EX1003 ¶¶346-347. Goldberg’s graph includes SNOMED “is-a” edges (e.g., Bacterial Pneumonia is-a Infective Pneumonia is-a Pneumonia) and “Is a” or “Sub-type” relations, and its diagnostic paths use SNOMED “type-of” relations. EX1006, 9:50-60, 10:3-53,

FIGS. 6-7, 9-11. Dang's hypernym-hyponym relationships between factual nodes provide additional support. EX1008 ¶¶[0010], [0047]-[0051].

7. Element [23f]: “wherein said medical terminology ontology includes a Systemized Nomenclature of Medicine–Clinical Terms (SNOMED-CT) database, or a Logical Observation Identifiers, Names, and Codes (LOINC) database”

Element [23f] is identical to element [1g]. *Supra* §IX.B.8; EX1003 ¶¶348-349. Goldberg describes SNOMED as “an encompassing Ontology covering hundreds of thousands of medical terms” and LOINC as “an ontology dedicated to laboratory tests and procedures,” and its laboratory-test entries use LOINC-coded names. EX1006, 1:54-56, 2:3-9, 6:5-34; FIG. 1.

8. Element [23g]: “one or more processors and memory that stores instructions”

Goldberg discloses the claimed one or more processors. Each of Goldberg's independent claims recites steps performed “by the at least one processor,” including “defining, by the at least one processor, one or more pathways on the medical knowledge graph” and “receiving, by the at least one process[or], the health data.” EX1006, 14:28-15:15, claims 9, 13. Goldberg's platform comprises “a computerized model that runs on a database for storage of medical hybrid knowledge graph” and “a diagnostic algorithm or software,” including “a cloud-based inference engine 210, communicatively coupled to a knowledge base 220.” EX1006, 7:10-20, 12:43-55, FIG. 2; EX1003 ¶351.

To the extent Goldberg does not expressly recite memory, a POSITA would have understood, and at minimum found obvious, that Goldberg's processor executes instructions stored in memory. Goldberg describes its application as software that "runs a file with instructions to execute commands to manage a patient through a diagnosis process," and its database and "diagnostic algorithm or software" require storage from which the processor reads data and code. EX1006, 2:45-47, 2:61-65, 12:43-55; EX1003 ¶352.

Gnanasambandam expressly discloses this conventional architecture: computing device 1400 includes "a processor 1402" and "a Random-Access Memory (RAM) 1420" that "stores instructions related to the operation of processes and applications executing on the computing device." EX1007, 40:13-27, 40:49-58, FIG. 14, claim 15; EX1003 ¶353.

Dang likewise discloses "one or more processors or processing units 16, a system memory 28," with program modules in memory that carry out its functions. EX1008 ¶¶[0063], [0066]-[0067]; EX1003 ¶354.

In the combined system, instructions stored in memory and executed by these processors perform the functions of elements [23h]-[23j]. EX1003 ¶355.

9. Element [23h]: “receive, via an application programming interface (API), a medical query from a software application”

Element [23h] corresponds to element [1a]. *Supra* §IX.B.2; EX1003 ¶¶356-357. Goldberg’s App 230 sends patient inputs and comparison questions to inference engine 210, and Gnanasambandam’s back-end component 9104 “is configured to publish one or more APIs 9103” that client device 9106 subscribes to and invokes. EX1006, 7:12-47, 9:1-20, FIG. 2; EX1007, 100:24-47, FIGS. 91-92.

10. Element [23i]: “identify, using said reasoning capability, a set of ancestor–descendant relationships ... relevant to said medical query”

Element [23i] corresponds to element [1h]. *Supra* §IX.B.9; EX1003 ¶¶358-359. Goldberg selects query-specific pathways using connectors that include SNOMED “is-a” and “type-of” relations, returns a “path to decision,” and searches “multiple pathways” to identify relevant findings and laboratory tests; Dang matches the patient complaint to graph nodes and infers evidential nodes “through hyponymy.” EX1006, 8:31-47, 11:55-67, 14:35-46, 16:22-45; EX1008 ¶¶[0009]-[0010], [0047]-[0051].

11. Element [23j]: “output, responsive to said medical query, an output to said software application ... in order for said software application to generate a medical determination”

Element [23j] corresponds to element [1i]. *Supra* §IX.B.10; EX1003 ¶¶360-361. Goldberg generates “one or more differential diagnoses for suspected disorders” and a next-best step, such as recommending “test A over test B,” and

Gnanasambandam's APIs deliver analytics, including diagnosis-related data, to consuming client applications. EX1006, Abstract, 7:25-56, 8:20-32; EX1007, 100:24-34, 101:12-37, 102:22-24, 101:66-102:5, 62:13-15.

W. Claim 24: “each investigation node is linked to a corresponding result node”

Claim 24 adds dependent claim 2's result-node relationships to the system of claim 23. Goldberg's database stores laboratory-test relationships and results, and Dang's distinct Observation Item and Lab Test and Check nodes provide an explicit implementation. EX1006, FIGS. 1, 4; EX1008 ¶¶[0027], [0036]. Claim 24 is therefore unpatentable for the reasons stated for claims 2 and 23. *Supra* §§IX.C, IX.V; EX1003 ¶¶362-363.

X. Claim 25: “said finding nodes are diagnostic factor nodes”

Claim 25 adds dependent claim 4's diagnostic-factor limitation. Goldberg's symptom and sign nodes are clinical observations used to generate suspected diseases and, therefore, are diagnostic factor nodes. EX1006, 7:25-47, FIGS. 4, 10. Claim 25 is therefore unpatentable for the reasons stated for claims 4 and 23. *Supra* §§IX.E, IX.V; EX1003 ¶¶364-365.

Y. Claim 26: “each investigation node does not include information specific to a medical condition”

Claim 26 adds dependent claim 8's separation of reusable investigation identity from condition-specific information. Goldberg's LOINC-coded test nodes

are reusable across disease pathways, while probabilities and relationship types reside on the associated records or paths. EX1006, 6:10-34; FIG. 1. Claim 26 is therefore unpatentable for the reasons stated for claims 8 and 23. *Supra* §§IX.I, IX.V; EX1003 ¶¶366-367.

Z. Claim 27: “each investigation node is disambiguated across said plurality of medical condition nodes”

Claim 27 adds dependent claim 9’s cross-condition disambiguation. Goldberg’s dedicated, standardized LOINC test nodes retain one identity while being linked to different conditions. EX1006, 6:12-34; 16:8-24. Claim 27 is therefore unpatentable for the reasons stated for claims 9 and 23. *Supra* §§IX.J, IX.V; EX1003 ¶¶368-369.

AA. Claim 28: “each investigation node is independent of said at least one ... medical condition node”

Claim 28 adds dependent claim 10’s reusable investigation-node architecture. Goldberg’s same laboratory-test node participates in pathways to multiple diseases, and Dang’s separate test tier confirms that the test identity is independent of any single condition. EX1006, 16:8-24; EX1008 ¶¶[0027]-[0031]. The claim is therefore unpatentable for the reasons stated for claims 10 and 23. *Supra* §§IX.K, IX.V; EX1003 ¶¶370-371.

BB. Claim 29: “a data structure different from said each investigation node ... including attributes pertaining to said ... medical condition nodes”

Claim 29 adds dependent claim 11’s intermediate data structure. Goldberg’s rule records and Dang’s feature nodes are distinct from the investigation node, connect the investigation to the condition, and carry probabilities or other condition-specific attributes. EX1006, FIG. 1; EX1008 ¶¶[0028]-[0031], FIG. 1B. Claim 29 is therefore unpatentable for the reasons stated for claims 11 and 23. *Supra* §§IX.L, IX.V; EX1003 ¶¶372-373.

CC. Claim 30: “at least one of said investigation nodes is traversable to at least two of said medical condition nodes”

Claim 30 adds dependent claim 12’s multi-condition traversability and condition-independent investigation. Goldberg’s laboratory-test pathways and Dang’s test-to-feature-to-multiple-disease paths meet both requirements. EX1006, 16:8-24; EX1008 ¶[0031], FIG. 1B. Claim 30 is therefore unpatentable for the reasons stated for claims 12 and 23. *Supra* §§IX.M, IX.V; EX1003 ¶¶374-375.

DD. Claim 31: “a ranking value indicating how likely it is that an investigation ... is indicative of a medical condition”

Claim 31 adds dependent claim 13’s ranking value. Goldberg’s probabilities and likelihood ranges rank the strength of the investigation-condition relationship and drive its diagnostic inference. EX1006, FIGS. 1, 4; 5:67-6:7, 6:10-60, 8:12-40.

Claim 31 is therefore unpatentable for the reasons stated for claims 13 and 23. *Supra* §§IX.N, IX.V; EX1003 ¶¶376-377.

EE. Claim 32: “at least one condition-dependent attribute of a medical condition”

Claim 32 adds dependent claim 14’s condition-dependent attribute. Goldberg’s rule types and rates vary with the associated condition, and Dang’s P(f|d) is expressly defined for a disease-feature pair. EX1006, FIG. 11; EX1008 ¶[0031]. Claim 32 is therefore obvious for the reasons stated for claims 14 and 23. *Supra* §§IX.O, IX.V; EX1003 ¶¶378-379.

FF. Claim 33: “said knowledge graph includes more than twenty thousand nodes”

Claim 33 adds dependent claim 21’s node-count requirement to the system of claim 23. As previously discussed, Goldberg’s SNOMED-based graph covers hundreds of thousands of medical terms and is designed for ongoing expansion. EX1006, 1:54-2:1, 6:10-34, 7:48-8:8. Routine scaling would have been obvious. Claim 33 is therefore unpatentable for the reasons stated for claims 21 and 23. *Supra* §§IX.T, IX.V; EX1003 ¶¶380-381.

GG. Claim 34: “said knowledge graph includes more than one hundred thousand nodes”

Claim 34 adds dependent claim 22’s node-count requirement to the system of claim 23. As previously discussed, Goldberg’s SNOMED ontology alone covers hundreds of thousands of terms, and the hybrid graph adds LOINC and clinical

relationships. EX1006, 1:54-2:1, 6:10-34, 7:48-8:8. Routine scaling would have been obvious. Claim 34 is therefore unpatentable for the reasons stated for claims 22 and 23. *Supra* §§IX.U, IX.V; EX1003 ¶¶382-383.

X. Ground 2: Claims 15-16 are Obvious Over Goldberg, Gnanasambandam, Dang, and Datla

A. Motivation to Combine

As explained for Ground 1, Goldberg and Gnanasambandam, with Dang, provide a knowledge-graph diagnostic system accessible through published APIs. *Supra* §IX.A. Goldberg supplies the hybrid knowledge graph integrating clinical data with SNOMED and LOINC, the diagnostic algorithm that traverses pathways to generate differential diagnoses, and the Patient Management App through which clinicians interact with the system. EX1006, Abstract, 6:5-28, 7:25-50. Gnanasambandam supplies the API layer through which external software applications submit medical queries and receive structured outputs. EX1007, 100:24-40, 101:12-37; EX1003 ¶385.

Claims 15-16 add that the querying application is an NLP engine that receives verbatim text and produces the medical query. Goldberg's application receives patient data through structured user interfaces, and Gnanasambandam's autonomous multipurpose application subscribes to and invokes APIs, but neither expressly characterizes the querying application as an NLP engine. EX1003 ¶386. Datla fills that role.

Datla discloses a knowledge-graph clinical-diagnosis system built around “a natural language processing engine configured to extract the at least one patient symptom and at least one demographic parameter from the received natural language input,” which is then used to query a knowledge graph and identify “a ranked list of one or more medical conditions, diagnoses, treatments, and/or tests for the patient.” EX1005, claim 1, Abstract, ¶¶[0006]-[0008], [0028]; EX1003 ¶¶123, 387. Datla’s NLP engine does not duplicate or interfere with Goldberg’s graph and reasoning or Gnanasambandam’s API. EX1003 ¶387.

A POSITA would have been motivated to add Datla’s NLP engine to the Goldberg-Gnanasambandam combination because Datla, like those references, is directed to knowledge-graph clinical decision support and it addresses the specific problem of accepting a clinician’s natural-language description of a patient and converting it into structured queries against a knowledge graph. EX1005 ¶¶[0001], [0005]-[0006], [0052], [0055]; EX1003 ¶388. Clinicians naturally describe patients in free text, and Goldberg already matches extracted symptoms, signs, and laboratory results to graph nodes. EX1006, 7:25-47; EX1003 ¶388.

The combination would have been predictable. Datla’s NLP engine produces structured output that translates directly into API query parameters, so connecting it to Gnanasambandam’s published APIs requires no inventive modification. EX1005, Abstract, ¶¶[0006]-[0008], claim 1; EX1003 ¶¶389-390. Each reference is an

implemented, individually described system used for its known purpose: Goldberg for the knowledge graph and diagnostic reasoning, Gnanasambandam for API deployment, Dang for graph topology and next-inquiry generation, and Datla for NLP-based query generation. EX1003 ¶¶390-391. A POSITA therefore would have reasonably expected the combined system to work as intended. *Id.*

B. Claim 15

Claim 15 adds three requirements to claim 1: the querying software application is an NLP engine; the engine receives verbatim text and produces a medical query containing a patient diagnostic factor or medical condition; and the method matches that factor to a finding node or the condition to a medical condition node to produce the output. EX1003 ¶394.

The phrase “said matching a portion” appears without an antecedent in the claim. The clause in which this phrase appears defines the matching as “matching said patient diagnostic factor to said at least one of said finding nodes or matching said patient medical condition to said at least one of said medical condition nodes to produce said output.” EX1003 ¶¶393-394. Reading the language in context, a POSITA would understand it to require matching the patient diagnostic factor in the query to at least one finding node, or matching the patient medical condition to at least one medical condition node, to produce the output. EX1003 ¶¶392-394.

NLP engine receiving verbatim text. Datla's processor comprises "a natural language processing engine configured to extract the at least one patient symptom and at least one demographic parameter from the received natural language input," shown as NLP Engine 314 in FIG. 3. EX1005, claim 1, ¶¶[0006], [0028], [0052], [0065], [0075], [0081], FIGS. 3-5; EX1003 ¶395. Datla's NLP engine is configured to "receive natural language input from a user, the input comprising information about at least one patient symptom and at least one demographic parameter about the patient." EX1005 ¶[0007], claim 1. "[A] clinician, medical professional, or patient provides information to the automated system via a user interface," and "[t]he information is provided in natural language," whether spoken and converted to text or typed on "a mobile device, laptop, desktop, wearable device, home computing device, or any other computing device." EX1005 ¶¶[0050], [0074]; EX1003 ¶396.

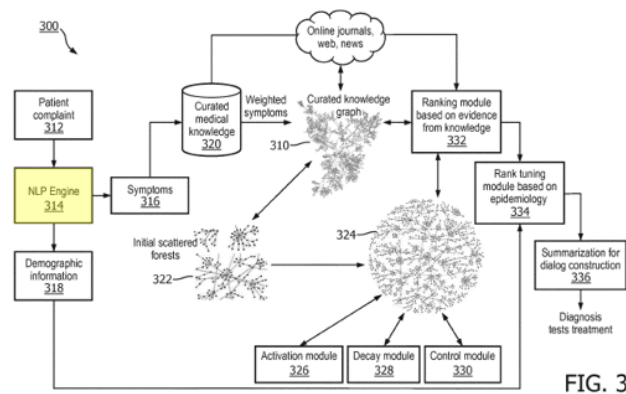


FIG. 3

EX1005, FIG. 3 (annotated)

Producing a medical query with a patient diagnostic factor or condition.

Datla's NLP engine "extract[s] the at least one patient symptom and at least one

demographic parameter from the received natural language input” and further extracts “keywords related to symptoms, such as signs, lab results, procedures and demographic information.” EX1005 ¶¶[0006]-[0007], [0015], [0028], [0052], claim 1. The system then “queries the knowledge [graph] using the extracted one or more patient symptoms.” EX1005 ¶[0055]. Each extracted symptom is a patient diagnostic factor, e.g., signs and symptoms a physician can observe or a patient can describe, and the extracted symptoms, signs, and laboratory results together form the medical query. EX1001, 9:21-28; EX1003 ¶397.

Matching to produce the output. Datla’s knowledge graph has “symptoms as root nodes connected by edges to the diseases and medical conditions associated with those symptoms.” EX1005 ¶[0036]. Datla assigns activation weights to the graph nodes corresponding to the extracted symptoms, expands outward from those symptom root nodes through connected nodes to generate a “diagnosis graph as a subset of the knowledge graph,” and identifies “a ranked list of one or more medical conditions, diagnoses, treatments, and/or tests for the patient from the diagnosis graph.” EX1005 ¶¶[0007]-[0008], [0055]-[0057], claim 1, FIG. 3. That is matching the patient diagnostic factor to finding nodes (symptom root nodes), and the patient medical condition to condition nodes, to produce the output. EX1003 ¶398.

In the combination, Datla’s NLP engine is the claimed software application as it receives verbatim text, extracts the diagnostic factors, and sends the structured

query through Gnanasambandam's API to Goldberg's knowledge graph, which matches the factors to finding and condition nodes using Goldberg's diagnostic algorithm (*supra* §IX.S) and returns the output through the API to generate a medical determination. EX1006, 7:25-47; EX1007, 100:24-34, 101:12-37, 102:22-24, 101:66-102:5, 62:13-15; EX1005 ¶¶[0062]-[0064]; EX1003 ¶399.

C. Claim 16

Claim 16 requires that the NLP engine be "initialized with at least one of said plurality of finding nodes from said knowledge graph in order to facilitate said matching." Datla assigns the symptom weight as an activation weight "to a node of the knowledge graph comprising the extracted one or more patient symptoms," and its initial forest starts from "root nodes associated with the extracted and weighted one or more symptoms." EX1005 ¶¶[0055], [0067]. For that step to work, the NLP engine's output must correspond to the graph's symptom (finding) nodes. EX1003 ¶401. Datla's activation-decay process likewise begins at the symptom root nodes that match the extracted concepts and spreads to connected disease nodes, confirming that the NLP output is designed to match the graph's finding nodes. EX1005 ¶¶[0036], [0055]-[0057], [0067]; EX1003 ¶404.

A POSITA would have found it obvious to initialize Datla's NLP engine with the finding nodes of Goldberg's hybrid graph. Because Datla's query begins at graph nodes that match the extracted symptoms, an extracted term that does not match a

node cannot start the query. EX1005 ¶¶[0055], [0067]; EX1003 ¶403. Goldberg's graph contains standardized symptom and sign nodes, and its diagnostic algorithm matches patient clinical terms to those nodes. EX1006, 6:10-34, 7:25-47, 16:8-24, FIGS. 4, 10; EX1003 ¶402. Loading the graph's finding-node terms into the NLP lexicon was the simplest, routine way to ensure that extracted concepts matched existing nodes, and doing so would facilitate the claimed matching without changing Datla's NLP process or Goldberg's diagnostic algorithm. EX1003 ¶403.

Claims 15 and 16 are therefore obvious over the combined teachings. Datla supplies the natural-language front end, Goldberg supplies the medical knowledge graph and diagnostic matching, and Gnanasambandam supplies the API through which the NLP application communicates with that graph. The combination uses known components for their disclosed purposes and would have produced predictable results. EX1003 ¶¶384-404.

XI. Ground 3: Claims 1-34 are Unpatentable Under 35 U.S.C. § 101

The Challenged Claims are directed to the abstract idea of collecting medical information, organizing it in a knowledge graph, reasoning over it using hierarchical relationships among medical concepts, and providing the results (the "Abstract Idea"). EX1003 ¶¶405, 408. The claims implement the Abstract Idea with conventional computer components and add no inventive concept. EX1003 ¶437.

A. Legal Standard

Abstract ideas are not patentable. *Alice Corp. Pty. v. CLS Bank Int'l*, 573 U.S. 208, 216-18 (2014). Under *Alice*, the Board first determines what the claim is “directed to.” *Id.* at 219. If the claim is directed to an abstract idea, the Board examines the claim elements, individually and as an ordered combination, for an “inventive concept” sufficient to transform the abstract idea into a patent-eligible application. *Id.* at 217-18, 221. “[M]erely requir[ing] generic computer implementation[] fail[s] to transform that abstract idea into a patent-eligible invention.” *Id.* at 221.

The Board applies this framework through the Office’s eligibility guidance. *Nabors Drilling Techs. USA, Inc. v. Motive Drilling Techs., Inc.*, PGR2022-00055, Paper 27 at 17-18 (PTAB Feb. 22, 2024). Under Step 2A, Prong One, the Board asks whether the claim recites a judicial exception, such as a mental process. Under Prong Two, the Board identifies the elements recited beyond the exception and asks whether they integrate the exception into a practical application. If they do not, Step 2B asks whether those additional elements are more than well-understood, routine, and conventional activity.

B. Independent Claim 1

1. Step 1

Claim 1 recites a method, which is a statutory process.

2. Step 2A, Prong One: Claim 1 Recites an Abstract Idea

Claim 1 sets forth each part of the Abstract Idea. EX1003 ¶406.

Abstract Idea	Claim Element(s)
Collecting medical information	[1a] receiving a medical query; [1e] nodes “extracted from a plurality of medical evidence sources”
Organizing medical information in a knowledge graph	[1b]-[1d] condition, finding, and investigation nodes linked by traversable relationships; [1e], [1g] linked to SNOMED-CT or LOINC
Reasoning over the knowledge graph hierarchically	[1f], [1h] identifying ancestor-descendant relationships relevant to the query by traversing the graph
Providing the results	[1i] outputting data about the relevant nodes

These steps collect and manipulate information, which the Federal Circuit has repeatedly held abstract. *Content Extraction & Transmission LLC v. Wells Fargo Bank, N.A.*, 776 F.3d 1343, 1347 (Fed. Cir. 2014); *Elec. Power Grp. LLC v. Alstom S.A.*, 830 F.3d 1350, 1353-54 (Fed. Cir. 2016); *In re Killian*, 45 F.4th 1373, 1380 (Fed. Cir. 2022). Limiting the information to medical conditions, findings, and investigations does not make the idea less abstract. *Elec. Power Grp.*, 830 F.3d at

1353; *Univ. of Fla. Rsch. Found., Inc. v. Gen. Elec. Co.*, 916 F.3d 1363, 1367 (Fed. Cir. 2019).

The recited steps are also mental processes. The Examiner found that they recite “observation, evaluation, and judgement that can be practically performed by a human, either mentally or with the use of pen and paper.” EX1002, 88-89; EX1003 ¶108. Clinicians and medical informaticists have long reviewed the literature and identified diagnostic factors and tests associated with conditions. EX1003 ¶409. They then organized those relationships in structured taxonomies and used hierarchical terminologies to reason about related concepts. *Id.* The claimed “reasoning capability” is the same reasoning a clinician uses on observing “double quotidian fever” and looking up the broader concept “fever” to identify associated conditions. EX1003 ¶411. The specification describes the same operation: inferring that a patient with “acute fever” also has “fever” by “walking the relevant ancestor-descendant chains” of SNOMED. EX1001, 8:37-58, 23:61-24:15; EX1003 ¶100. Steps that “can be performed in the human mind” or “using a pencil and paper” are “a telltale sign of abstraction.” *PersonalWeb Techs. LLC v. Google LLC*, 8 F.4th 1310, 1316 (Fed. Cir. 2021).

The specification confirms that the Abstract Idea is the focus of the claims. It concedes that publishers “such as DynaMed, BMJ, UpToDate” already assembled published evidence for diagnosis through “human-centric activity.” EX1001, 1:56-

2:5; EX1003 ¶¶94. The alleged advance is doing the same thing in “computational” form. *Id.* The claims therefore focus on making medical evidence accessible and queryable, not on improving computer technology. EX1003 ¶¶408.

3. Step 2A, Prong Two: No Practical Application

Beyond the Abstract Idea, claim 1 recites only three additional elements: (1) the “application programming interface (API)” and “software application” that send and receive the query and output; (2) the knowledge graph as a stored data structure; and (3) the requirement that the output enable the software application “to generate a medical determination.” EX1001, claim 1. The node relationships, SNOMED-CT/LOINC linkage, and ancestor-descendant traversal are part of the Abstract Idea, not additional elements. Considered individually and in combination, the additional elements do not integrate the Abstract Idea into a practical application.

API and software application. The claim recites the API only as a means of exchanging data and describes it purely by function. EX1001, claim 1. The specification describes no API structure or technique; it lists only “FHIR, USCDI (United States Core Data for Interoperability), CDS Hooks, and vendor-specific APIs.” EX1001, 6:4-8; EX1003 ¶¶101, 412. Receiving a query and returning results through such an interface is a “mere instruction[] to apply the exception using a generic computer component.” *See VeriPath, Inc. v. Didomi*, 842 F. App’x 640, 643 (Fed. Cir. 2021) (explaining claims that “utilize[] an API to achieve the desired

result” were abstract). The Examiner likewise found that receiving via an API and outputting to a software application were “insignificant extra-solution activity.” EX1002, 89-90; EX1003 ¶108.

Knowledge graph. The claim does not recite a particular way of storing or retrieving the graph. EX1001, claim 1. The specification states that the database may be “[a]ny of a wide variety of other types of databases ... such as a relational database or object store or object-oriented database,” including a JanusGraph database. EX1001, 8:10-22; EX1003 ¶410. “[A]n improvement to the information stored by a database is not equivalent to an improvement in the database’s functionality.” *BSG Tech LLC v. Buyseasons, Inc.*, 899 F.3d 1281, 1288 (Fed. Cir. 2018).

Output limitation. The requirement that the output enable the application “to generate a medical determination” states only the intended use of the data. EX1003 ¶425. This requires no diagnosis, treatment, or other action and constitutes insignificant post-solution activity because it does not reach any physical process and only returns data to other software. It is merely insignificant post-solution activity that is insufficient to transform the Abstract Idea into a patentable process.

No technological improvement. The claims do not improve the functioning of a computer, a database, an API, or any other technology. EX1003 ¶408. No claimed element changes how any component operates: the claims merely use a computer to collect, analyze, and return data, which is insufficient.

The prosecution history does not reveal any practical application. The Examiner initially rejected all claims under § 101. EX1002, 88-90; EX1003 ¶¶108, 413. The Examiner found that, apart from “an application programming interface (API)” and “a computer system comprising one or more processors and memory,” nothing precluded performing the steps mentally. *Id.* The applicant then added the “medical determination” output limitation and argued that “a human cannot implement a software application in his or her mind in order to access a knowledge graph via an API.” EX1002, 54-55, 58-59; EX1003 ¶¶111-112. The Examiner allowed the claims on that rationale alone. EX1002, 16-17; EX1003 ¶¶115, 426.

That rationale is legally wrong. The question is whether the claim as a whole is directed to an abstract idea, not whether a human can literally execute an API. EX1003 ¶414. *See Oasis Tooling, Inc. v. Siemens Indus. Software Inc.*, No. 2024-2085, 2026 WL 537372, at *2 (Fed. Cir. Feb. 26, 2026) (“[i]t is immaterial to the patent eligibility analysis that human minds are unable to parse, standardize, and digest the data like a computer”); *Content Extraction*, 776 F.3d at 1347. The same Examiner, in a related application, found the same API limitation to be “a generic computer component that [is] used as a tool in performing generic computer functions of accessing the graph database to generate [a] healthcare determination.” EX1014, 116-128.

For the foregoing reasons, when considered individually or in combination, the recited elements beyond the Abstract Idea fail to integrate the exception into a practical application.

4. Step 2B: No Inventive Concept

The additional elements, individually and as an ordered combination, are well-understood, routine, and conventional. EX1003 ¶¶420, 436. Elements that are part of the Abstract Idea do not provide an inventive concept. *BSG Tech*, 899 F.3d at 1290-91. That includes the SNOMED-CT/LOINC linkage and ancestor-descendant traversal. *Id.* Those features are, in any event, also conventional.

API. Exposing a medical knowledge base through APIs was a well-established design pattern. EX1003 ¶¶87-89, 412, 424. BioPortal has provided RESTful APIs to query SNOMED-CT and LOINC since 2006, and the National Library of Medicine’s UMLS and HL7’s FHIR standard provided terminology-service APIs. EX1003 ¶88; *supra* §V.D. Gnanasambandam publishes APIs that “perform analytics based on a knowledge graph” for client applications. EX1007, 100:24-34, 101:12-37; EX1003 ¶424. The ’883 patent only discloses off-the-shelf FHIR, USCDI, and CDS Hooks APIs. EX1001, 5:52-54, 6:4-6. An API is no different from the generic “interactive interface” held insufficient in *Intellectual Ventures I LLC v. Capital One Bank (USA)*, 792 F.3d 1363, 1369-70 (Fed. Cir. 2015).

Knowledge graph and database. Medical knowledge graphs with condition, finding, and investigation nodes were well established. EX1003 ¶¶74-83, 421. Goldberg discloses “a healthcare knowledge graph database for storing a medical hybrid knowledge graph.” EX1006, Abstract; EX1003 ¶120. Dang discloses a multi-tier diagnostic knowledge graph. EX1008 ¶¶[0027]-[0031]; EX1003 ¶122. The specification permits any database type, including an off-the-shelf JanusGraph database. EX1001, 8:10-22; EX1003 ¶421. “[A] database” is a “generic computer element[.]” *Intell. Ventures I*, 792 F.3d at 1368.

Ontology and reasoning. SNOMED-CT and LOINC are pre-existing third-party vocabularies that had been widely used for decades. EX1003 ¶¶59-68, 422; *supra* §V.A. Goldberg integrates both. EX1006, 6:5-28; EX1003 ¶422. SNOMED-CT’s polyhierarchy was designed for ancestor-descendant traversal, and reasoning systems had long used it to generalize and specialize clinical queries. EX1003 ¶¶90-91, 423. The specification concedes that SNOMED-CT, LOINC, and RxNORM are existing ontologies. EX1001, 4:12-20, 5:13-19; EX1003 ¶99. The ’883 patent does not claim a new traversal algorithm. EX1003 ¶423. Claims that do “not even require a new source of information, or new techniques for analyzing it” lack an inventive concept. *Elec. Power Grp.*, 830 F.3d at 1355.

Output. Returning differential diagnoses or next-best actions to an application through an API is not a technical improvement and specifies no mechanism. EX1003 ¶425.

Ordered combination. Considered together, a software application sends a query through an API, the system traverses a conventional ontology stored in a conventional database, and the API returns results. That is “no more than the sum of [its] parts.” *Nabors*, Paper 27 at 30-31; EX1003 ¶436. Claims requiring nothing more than “conventional, generic technology” to gather, analyze, and transmit data lack an inventive concept. *Elec. Power Grp.*, 830 F.3d at 1356. Any gain in speed or efficiency from automation is likewise insufficient to confer eligibility. *Intell. Ventures I*, 792 F.3d at 1367; *Recentive Analytics, Inc. v. Fox Corp.*, 134 F.4th 1205, 1214-15 (Fed. Cir. 2025).

C. Independent Claim 23

Claim 23 recites a system that performs the same functions as claim 1. EX1001, claim 23; EX1003 ¶407. Claim 23 recites a machine (Step 1), but recites the same Abstract Idea as claim 1 (Prong One). EX1003 ¶407. Claim 23 adds only “a database that stores a knowledge graph” and “a computer system comprising one or more processors and memory that stores instructions.” EX1003 ¶407.

Those components are recited at a high level of generality and are no more than instructions to apply the Abstract Idea on a computer (Prong Two). *Alice*, 573

U.S. at 221-23. The specification describes these components in generic terms: a computer system that “may have many physical forms,” from a handheld device to a personal computer. EX1001, 31:60-67, FIGS. 11A-11B; EX1003 ¶¶407. Processors and memory that store, process, and transmit data are well-understood, routine, and conventional (Step 2B). EX1003 ¶¶435; *Alice*, 573 U.S. at 226; *Nabors*, Paper 27 at 30. Goldberg, Gnanasambandam, and Dang all disclose such components. EX1006, 12:43-55; EX1007, 40:13-27, 40:49-58; EX1008 ¶¶[0063], [0066]-[0067]; EX1003 ¶¶351-354. Claim 23 is ineligible for the same reasons as claim 1.

D. Dependent Claims 2-22 and 24-34

The dependent claims add details about the content, scale, source, and handling of the data. EX1003 ¶¶415-419. Each group either further describes the Abstract Idea (Prong One) or adds a generic, conventional element that neither integrates the Abstract Idea into a practical application (Prong Two) nor supplies an inventive concept (Step 2B). EX1003 ¶¶419, 427.

Graph content and structure (claims 2-4, 8-14, 24-32). These claims add result nodes, diagnostic factor nodes, condition-independent investigation nodes, and data structures, ranking values, or condition-dependent attributes on the paths between nodes. EX1003 ¶¶416. They describe how information is organized, which is part of the Abstract Idea. *Content Extraction*, 776 F.3d at 1347. Storing one reusable entry per test, with condition-specific information kept elsewhere, is a

standard data-organization choice. EX1003 ¶428. Recording how strongly a test indicates a condition adds no technical mechanism. EX1003 ¶429. The specification states that these elements “need not necessarily be implemented . . . as nodes.” EX1001, 18:5-9; EX1003 ¶274. Goldberg’s rule records and Dang’s feature nodes confirm that these structures were conventional. *Supra* §§IX.C-E, IX.I-O, IX.W-AE; EX1003 ¶¶214-232, 258-309, 362-379.

Querying application (claims 5, 15-16). An “AI application” is a well-known application type. EX1003 ¶431; *supra* §§IX.F, X.B-C. Gnanasambandam’s AI-based application invokes knowledge-graph APIs. EX1007, 18:30-36; EX1003 ¶236. For claims 15-16, the specification describes its NLP processes as conventional techniques. EX1001, 7:55-8:5; EX1003 ¶¶98, 431. The specification describes initializing the NLP engine with graph nodes only as a preference, without any technique for doing so. EX1003 ¶431. Datla discloses an NLP engine that extracts symptoms and queries a knowledge graph. EX1005 ¶¶[0006]-[0008], [0055]; EX1003 ¶¶387-388.

Matching, output, and iteration (claims 6-7, 17-20). Matching patient information to nodes (claims 6 and 20) is the Abstract Idea itself. EX1003 ¶432. Identifying findings not yet elicited (claim 7) is the ordinary next step in differential diagnosis, and the claim recites no technique for doing it. EX1003 ¶433. Displaying output (claim 17) and outputting a data structure (claim 18) are generic computer

functions. *Id.*; *Elec. Power Grp.*, 830 F.3d at 1354. Repeating the query with new information (claim 19) applies the same idea again. EX1003 ¶434; *supra* §§IX.G-H, IX.P-S.

Node-count thresholds (claims 21-22, 33-34). These claims specify only the scale of stored data, and the '883 patent gives them no technical significance. EX1003 ¶430. A database with 100,000 entries is directed to the same abstract idea as one with 100 (or any other number). *Intell. Ventures I*, 792 F.3d at 1367.

Each system claim is ineligible for the reasons given for its method counterpart. EX1003 ¶435. Claims 1-34 are therefore unpatentable under 35 U.S.C. § 101.

XII. CONCLUSION

For at least the foregoing reasons, the challenged claims are unpatentable.

Respectfully submitted,

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CERTIFICATION OF WORD COUNT

Pursuant to 37 C.F.R. § 42.24(d), the undersigned hereby certifies that the foregoing Petition for Post Grant Review is produced using a 14-point Times New Roman font and contains approximately 18,274 words, which is less than the 18,700 total words permitted by the U.S. Patent Trial and Appeal Board rules. Counsel relies on the word count of the computer program used to prepare the Petition on October 5, 2026.

Dated: October 5, 2026

By: /s/ Angelo J. Christopher

Lead Counsel for Petitioner

CERTIFICATE OF SERVICE

The undersigned hereby certifies that a copy of the foregoing Petition for Post Grant Review, together with all exhibits filed therewith, was served on October 5, 2026, by Priority Mail Express at the correspondence address of record for the '883 patent in the USPTO Patent Center:

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